

# Efficient Market Hypothesis and Calendar Effects: Evidence from the Oslo Stock Exchange

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# Summary

Stock market efficiency is an essential property of the market. It implies that rational, profit-maximizing investors are not able to consistently outperform the market since prices of stocks in the market are fair, that is, there are no undervalued stocks in the market. Market efficiency is divided into three forms: weak, semi-strong and strong. Weak form of market efficiency implies that technical analysis, utilizing historical data, cannot be used to predict future price movements, since all the historical information is impounded into the stock prices and price changes are random. Semi-strong form of market efficiency states that fundamental analysis does not create opportunity to earn abnormal returns, since all publicly available information is reflected in the stock prices. In market efficiency in its strong form, the price on stock reflects all the relevant information and knowledge of insider information will not create opportunity to earn abnormal returns.

In practice, to have a perfectly efficient market is almost impossible. Investors do not always behave rationally, stocks can be priced «wrongly» due to presence of anomaly in price formation process or there can emerge a predictable pattern in stock price changes. All these distortions lead to less efficiency or inefficiency of the market and provide opportunity of arbitrage or profiting from abnormal returns. There are three types of market anomalies: technical, fundamental and calendar. Technical and calendar anomalies relate to the weak form of market efficiency, whereas fundamental anomalies relate to the semi-strong form of market efficiency. Technical anomalies create predictability in stock price changes, that can be detected through technical analysis of the historical information. Fundamental anomalies create predictability in stock price changes that can be found through fundamental analysis of the publicly available information. Calendar anomalies generate seasonality in stock returns, that occur to be systematic and consequently creates opportunity to predict future price movements.

In this thesis weak form of market efficiency of the Oslo Stock Exchange and presence of calendar anomalies in stock price changes are analyzed. Weak form of market efficiency and calendar anomalies at the Oslo Stock Exchange were also examined in previous works, but the data that was utilized for analysis is prior to the crisis 2008-2009. Here, presence of the calendar effects at Oslo Stock Exchange, namely day-of-the-week, turn-of-the-month, intra-month, turn-of-the-year and holiday effects, is analyzed for two periods, that is, before and after crisis. The data consists of closing prices on OSEAX Oslo Børs All Share Index,

OBX Total Return Index and OSESX Oslo Børs Small Cap Index, where each index describes the market as a whole, the part of the market with the most liquid companies and the part of the market with the smallest companies, respectively.

Weak form of market efficiency has a relevance to the Random Walk Hypothesis, that mainly states that returns are independent and unpredictable, that is, they follow a random walk process. Thereby, the weak form of market efficiency is checked with application of the Lo and MacKinlay's Variance Ratio test, the Cumby-Huizinga autocorrelation test and the Phillips-Perron unit root test. The results support a random walk hypothesis for the OBX and OSEAX indices returns, that provides evidence of weak form efficiency of these parts of the market. For returns on the small cap index, there was found a diminishing positive serial correlation, that is likely to be caused by infrequent trading. Due to the presence of the serial correlation in returns on the small cap index it is not possible to conclude upon random walk behavior of the prices, whereas results from the unit root test, that accounts for serial correlation, support the hypothesis that log prices on the small cap index have a unit root. Thus, the part of the market with small cap companies exhibits less efficiency.

To test the presence of the calendar anomalies on the market, the methodologies suggested by Borges (2009), Nikkinen et al (2007) and Szakmary and Kiefer (2004) were adopted with minor modifications. The methodology applied to the returns on the Oslo Stock Exchange indices relies on the estimation of an EGARCH(1,1)-t model and application of the non-parametric Kruskal-Wallis test to detect presence of the calendar anomalies in the market. Furthermore, robustness of obtained results is verified with estimation of the regression with application of the bootstrap procedure, which helps to account for data mining bias.

The results suggest that there are no calendar anomalies in returns on the OBX and OSEAX indices in the post-crisis period, and anomalies that were reported in the pre-crisis period were short-term, providing support towards market efficiency. But anomalies found in the small cap index are persistent and remain significant for two tested periods. In particular, returns on the small cap index are observed to be significantly high on Friday, indicating Weekend effect, on the TOY period and on the last trading day before Christmas, indicating Holiday effect. Presence of persistent calendar anomalies in the small cap index could be caused by presence of high trading costs in the market, that reduces profits from exploiting of anomalies.

# Preface

The thesis is submitted in partial fulfillment of the requirements for the degree of Master of Philosophy in Economics in the Department of Economics at University of Oslo. The thesis has been made solely by author in close cooperation with supervisor professor Diderik Lund.

I would like to thank professor Diderik Lund for guidance, valuable comments and essential advices throughout the work period. I am also grateful to professor D. Lund for introducing me the finance theory and inspiration he gave me for further studies of the field.

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# Content

1	Introduction .....	1
2	The market efficiency theory .....	3
2.1	A brief history of market efficiency .....	3
2.2	Literature related to Oslo Stock Exchange .....	4
2.3	Efficient Market Hypothesis.....	6
2.4	Random Walk Hypothesis .....	10
3	Market Inefficiency anomalies.....	12
3.1	Calendar effects .....	12
4	Methods and data .....	15
4.1	The Data .....	15
4.1.1	Descriptive statistics.....	15
4.2	Methodology.....	19
4.2.1	Random Walk Hypothesis testing .....	19
4.2.2	Calendar anomalies .....	22
5	Empirical results.....	29
5.1	Random walk hypothesis.....	29
5.2	Calendar effects .....	33
5.2.1	Day-of-the-week effect .....	33
5.2.2	Turn-of-the-month and intra-month effects .....	37
5.2.3	Turn-of-the-year effect .....	40
5.2.4	Holiday effect .....	42
6	Conclusion.....	44
	Bibliography.....	46



# 1 Introduction

The concept of the market efficiency implies that all available relevant information is reflected in the stock prices, making it impracticable to consistently outperform the market. It entails that the price changes are unpredictable since they are affected by news, which arrives randomly. The idea of random and unpredictable price changes was first introduced a century ago in the thesis of Bachelier (1900) and grew into the market efficiency concept, as it was denominated by Fama (1965). The market efficiency theory survived the critics that emerged in recent decades and is still of interest in research.

Market efficiency is divided into three forms based on the type of the information that is reflected in the stock prices. These are weak, semi-strong and strong forms of market efficiency. Weak form of efficiency implies that all historical information in the markets is comprised in the stock prices and analysis of past information does not help to predict future price movements. Semi-strong form of market efficiency states that all the publicly available information is incorporated in the stock prices. It relates to the idea that the stock prices instantaneously adjust to the arriving news. Strong form of market efficiency comprises both weak and semi-strong forms. It implies that all information, including not publicly available, is reflected in the stock prices.

At some point in time markets can exhibit some degree of inefficiency. This inefficiency is substantially caused by anomalies, that induce a predictable pattern in the market. Such anomalies can be classified in three categories, namely technical, fundamental and calendar. Fundamental anomalies relate to the semi-strong form of market efficiency. Fundamental analysis is intended to search for stocks that systematically outperform other stocks in the market. A typical example is that small cap stocks were found to consistently outperform large cap stocks. Technical and calendar anomalies have a relevance to the weak form of market efficiency. Technical anomalies create predictability in stock price changes, that can be utilized to earn abnormal returns through application of the analysis of historical information. Calendar anomalies relate to seasonality in the stock, that the stock price is systematically lower or higher within a particular calendar period.

The Efficient Market Hypothesis has important implications both for investors and firms. In the efficient market when news comes out it is instantly reflected in the stock prices, so that obtaining released information does not help an investor to beat the market.

Furthermore, since reflected information makes the price of the stock to be fair, firms cannot profit from deluding investors on the market.

In practice, efficiency of markets varies through different markets and different countries. There are few people who believe in the strong form of market efficiency, most people assume that markets are largely efficient and all the anomalies are short-term due to high competition and free entry conditions. This implies that all markets are efficient to different extents and there can be presence of anomalies that distort efficiency, but can be competed away once they are reported.

In this thesis, the weak form of market efficiency of Oslo Stock Exchange and presence of calendar anomalies in the market are investigated. Previous works on the market efficiency of Oslo Stock Exchange were utilizing the data prior to the crisis 2008-2009, whereas in this thesis presence of calendar anomalies is investigated for two periods, namely before and after crisis. The data consists of daily closing prices on OBX Total Return Index, OSEAX Oslo Børs All Share Index and OSESX Oslo Børs Small Cap Index with the range of 14 years of observations, that is, January 2000-December 2014. If Oslo Stock Exchange is informationally efficient, it implies that anomalies documented in previous research should be traded out and not anymore present in the market.

The weak form of market efficiency is tested with application of the Lo and MacKinlay's Variance ratio test, the Cumby-Huizinga autocorrelation test and the Phillips-Perron unit root test. The methodology for the calendar anomalies testing is adopted from the works of Borges (2009), Szakmary and Kiefer (2004) and Nikkinen et al (2007), who tested day-of-the-week, turn-of-the-year, turn-of-the-month and intra-month anomalies, respectively. These works are among the most recent in this field, so that they account for shortcomings of the previous methodologies. All the methodologies suggest application of ARCH-type models for modelling returns on the indices. Also, Borges (2009) suggested estimation of the regression model with application of the bootstrap procedure to account for data mining bias and application of a non-parametric Kruskal-Wallis test to check the equality of distribution of returns within particular calendar period. The results are estimated with application of the Statistical Software Stata 13.

The results provided evidence of weak form of market efficiency and short-term anomalies for the OBX and OSEAX indices, whereas OSESX index was shown to exhibit less efficiency and persistent calendar anomalies.

## 2 The market efficiency theory

### 2.1 A brief history of market efficiency

A concept of market efficiency was described in the PhD thesis in mathematics of Bachelier (1900) where he detected that commodity prices fluctuate randomly, but his work was disregarded for half a century. Further, Cowles (1933) analyzed the work of investment professionals and found that it is not possible to outguess the market. Complementary to Bachelier's findings, Working (1934) and Cowles and Jones (1937) independently of Bachelier's work concluded that US stock prices fluctuate randomly. In 1955 after receiving a postcard from Leonard Jimmie Savage regarding Bachelier's works, Paul Samuelson found a copy of Bachelier's thesis and from 1956 the theory of price behavior became of interest in economic research. Mandelbrot (1963) presented a new model of price behavior where he used natural logarithm of prices and Pareto distribution. Samuelson (1965) provided the concept of a martingale and proved that prices fluctuate randomly. Fama (1965) defined market efficiency and concluded that stock market prices follow a random walk. Roberts (1967) made a distinction between weak, semi-strong and strong forms of market efficiency, that were further used in Fama (1970) where he described market efficiency in terms of information efficiency: *"A market in which prices always 'fully reflect' available information is called 'efficient'"*. Malkiel (1973) wrote a book "A Random Walk Down Wall Street" where he argued that stock prices typically exhibit a random walk and it is impossible to consistently outperform the market. After most of papers and research were made in support of the random walk behavior of prices, there were several attempts to show the weakness of market efficiency (Beja (1977), Grossman and Stiglitz (1980), LeRoy and Porter (1981), Lo and MacKinlay (1988), Lehmann (1990), Jegadeesh (1990), etc.). During the last decades market efficiency theory was under debate. Several researchers found anomalies that distort market efficiency and create opportunities to generate trading rules (Ariel (1987), Cooper et al (2006), Agarwal and Tandon(1994), Cadsby and Torbey (2003), etc.). Also, De Bondt and Thaler (1985) showed that stock prices tend to overreact. Jegadeesh and Titman (1993) found that the contrarian strategy brings abnormal returns. Haugen (1995) found evidence of market inefficiency, he concluded that the short-term overreaction leads to long-term reversal. But at the same time there was made research in support of Efficient Market Hypothesis. Chan et al (1997) provided evidence of weak form market efficiency of

the world equity market. Zhang (1999) developed a theory of marginally efficient markets. Malkiel (2003) considered critics of market efficiency theory and concluded that some market imperfections can be present on the market to create incentive for investors to try to outperform the market, but all in all, markets are remarkably efficient with respect to utilization of information. Schwert (2003) classified anomalies that weaken market efficiency and concluded that publishing anomalies helps to improve market efficiency, based on strategies implemented by specialists. Malkiel (2005) showed that professional investment managers, both in U.S. and abroad, do not outperform index benchmarks and provided evidence that large market prices do seem to reflect all available information. Marshall et al (2010) tested over 5000 trading rules in 49 countries, concluded that when accounting for data-snooping bias, profits from technical trading rules are not greater than the one that is expected from random data fluctuation.

All in all, the theory of market efficiency survived the challenges introduced in research for several decades and is still considered as an important component of the finance world.

## **2.2 Literature related to Oslo Stock Exchange**

Jennergren and Korsvold (1974) investigated efficiency of Norwegian and Swedish stock markets. They analyzed 15 stocks traded on Oslo Stock Exchange for the period 1967-1971 with application of serial correlation analysis and Runs tests and found that the Norwegian stock market is not weak form efficient. They also rejected the hypothesis of the logarithmic returns to have a Normal distribution, in fact they had an extremely leptokurtic distribution. They noted that the Norwegian market is probably the smallest among those for which price behavior was investigated. They suggested that the inefficiency can be due to the small size of the market which implies that it is less technically organized and less amounts of information regarding firms and securities could be available. This conclusion would not be appropriate nowadays, when the Norwegian stock market is not regarded as a small market.

Boudreaux (1995) investigated presence of monthly effects in seven stock markets, including Norwegian stock market, for the time period 04.03.1978-30.12.1992. The author used paired t-test to test for the difference between returns at the beginning and at the end of the month. He also excluded the possibility of a January effect driving the result. There was

found end-of-the-month effect in Norwegian stock market, that is, significantly positive returns at the beginning of the month.

Skjeltorp (2000) examined the persistence of the Norwegian stock market and the distributional scaling behavior of the price variations. He applied the R/S (range over standard deviation) statistic on the daily closing prices of TOTX (Total index) at Oslo Stock Exchange for the time range 1983-1995 and found evidence of persistence in the Norwegian Stock market, that contradicts efficient market theory. He also used data on the OBX index for the time range 1990-1994 to investigate a distributional scaling behavior of prices and found that the empirical distribution is similar to a Levy distribution for price variations less than  $\pm 6$  standard deviations, so that he found evidence that the OBX index follows a scaling law.

Dai (2007) examined the turn-of-the-year effect at the Oslo Stock Exchange for the time range 1983-1999 years and found presence of turn-of-the-year effect at OSE characterized by abnormally high January returns. There was also found a support for the tax-related explanation of the anomaly through testing the tax-loss selling hypothesis.

Hansen, Lunde and Nason (2005) used stock indices from 10 countries, including Norway (OSEAX - Oslo Børs All Share Index, OSESX – Oslo Børs Small Cap Index, OBX Total Return Index), to test the calendar effects in equity returns. The data range used for the Norwegian indices was the smallest among other indices utilized for test, for OSEAX and OSESX: 29.12.1995-06.05.2002, for OBX: 03.01.1995-06.05.2002. They applied a generalized F-test on returns and standardized returns accounting for bootstrapping with the null hypothesis of no calendar effect conditioning on full universe of 181-calendar effects, 17-calendar effects and 5-calendar effects. The result showed that there is no evidence against a null hypothesis conditioning on 181- and 17-calendar effects for returns on the OBX and OSEAX indices, but the null hypothesis can be rejected at 1% significance level when conditioning on 5-calendar effects (such as pre- and post-holiday effects, end-of-the-year effects). For OSESX index returns the null hypothesis can be rejected at 1% significance level for all three cases. The results showed that there is presence of the calendar effects in the small cap index.

Sæbø (2008) examined anomalies in the Norwegian stock market. The author collected data for the OSEAX, OSESX, OSEBX, OBX indices for the time range July 1990-June 2005 and used the CAPM model to test the presence of the asset pricing model anomalies and calendar anomalies. The author found evidence of significant positive abnormal returns on Fridays and Thursdays, but the Thursday effect was not robust, also there

was found a January effect, that is, significant positive excess returns in January. The result held for all indices before 1996 and only for the OSESX index after 1996. Furthermore, there was found strong size and leverage effects in the Norwegian stock market.

Giovanis (2009) examined calendar anomalies in 55 stock markets in 51 countries, including Oslo Stock Exchange, with application of the GJR-GARCH model. He used data for the closing price series on the OSEAX index for the time range 08.02.2001-31.12.2008. It was found that returns in April, May and October were significantly positive. That determines the presence of the month-of-the-year effect at OSE that violates the EMH.

Borges (2009) revised the previous methodologies used to identify the calendar effects and proposed an application of the bootstrapping and GARCH model to determine the calendar effects. The author tested the hypothesis of the presence of calendar effects in stock exchanges of 17 countries, including Norway. To represent the Oslo Stock Exchange, the OSEAX All Share index for the time period January 1994 – December 2007 was utilized. There was found a presence of the day-of-the-week effect in the OSEAX index, namely positive excess returns on Friday, but all-in-all it was concluded that there is no strong evidence of cross-the-board calendar effects, since all of them are mostly country-specific.

Table 1 summarizes the literature review associated with the research made on the market efficiency and calendar effects at Oslo Stock Exchange (OSE, hereafter).

## **2.3 Efficient Market Hypothesis**

Market efficiency can be viewed in a different approach: allocatively efficient market in terms of allocation of the resources in the economy, socially efficient market in terms of social welfare, productively efficient market with respect to production cost and informationally efficient market with respect to information set. Here, we consider efficiency of the stock market that relates to the informational market efficiency and hence the Efficient Market Hypothesis.

The Efficient Market Hypothesis (EMH) implies that it is not possible to outperform the market, since all stocks are traded at their fair value, that is, there cannot be undervalued stocks in the market, because at any point in time stock prices fully reflect all the available relevant information. EMH assumes rational behavior of participants in the market, in particular Fama (1965a) defined efficient market as a market with rational profit-maximizing participants, who try to predict future price movements.



*Table 1. Summary of the literature review related to the Oslo Stock Exchange*

<b>Paper</b>	<b>Data</b>	<b>Time period</b>	<b>Methods</b>	<b>Conclusion</b>
<b>Jennergren and Korsvold (1974)</b>	15 stocks traded at OSE	1967-1971	Serial correlation analysis Runs tests	Evidence of no weak form market efficiency of Oslo Stock Exchange
<b>Boudreaux (1995)</b>	Capital International Perspective index	1978-1992	Linear regression and paired t-test	Evidence of end-of-the-month effect: significantly positive stock returns at the beginning of the month
<b>Skjeltorp (2000)</b>	TOTX OBX	1983-1995 1990-1995	R/S test Analysis of scaling behavior of prices	Evidence of persistence at OSE, OBX index follows a scaling law
<b>Dai (2003)</b>	Value-weighted index of OSE stocks	1984-1999	Linear regression	Evidence of turn-of-the-year effect that is influenced by changes in tax law
<b>Hansen, Lunde and Nason (2005)</b>	OSEAX, OBX, OSESX	1995-2002	Generalized F-test, Bootstrap procedure	Presence of the calendar effect in the small cap index (OSESX)
<b>Sæbø (2008)</b>	OSEAX, OSESX, OSEBX, OBX	1990-2005	CAPM model	Evidence of significant positive abnormal returns on Fridays and Thursdays (not robust), consistent January effect in OSESX index, strong size and leverage effects
<b>Giovanis (2009)</b>	OSEAX	2001-2008	GJR-GARCH model	Presence of the month-of-the-year effect at OSE
<b>Borges (2009)</b>	OSEAX	1994-2007	GARCH model, linear regressions with bootstrapped and robust standard errors	Presence of the day-of-the-week effect at OSE: positive excess returns on Friday

Market efficiency in terms of fully reflected available information in the prices was suggested by Fama (1970). According to Fama (1970), the sufficient conditions for market efficiency are:

- i. Absence of transaction costs in trading securities;
- ii. Information is costless and accessible to market participants;
- iii. Everyone agrees on implications of available information for the stock prices and the future distribution of stock prices.

In the market that reveals sufficient conditions, prices fully reflect all available information, that is, such market is informationally efficient. In real world it may be difficult to find a market that exhibits all mentioned conditions. But Fama (1970) mentioned that these conditions are sufficient, but not necessary. If one of the conditions is violated it does not necessarily lead to market inefficiency. The effect of the distortion created by violation of sufficient conditions is a main topic in research of market efficiency.

But in the last decades EMH was continuously challenged by the followers of Behavioral Finance who claim that markets are inefficient. They argue that investors do not necessarily behave rationally as it is often assumed in economic research and particularly in efficient market theory, on the contrary, many investors may exhibit irrational behavior. Also, investors may not perceive information equally and they may disagree on the future distribution of returns. Disproportional investors' reaction to the news may lead to the problem of over-reaction and under-reaction, which are inconsistent with EMH. However, there were also found anomalies and behaviors that could not be explained by behavioral finance theory. Fama (1998) asserted that many findings in behavioral finance contradict each other and in general, behavioral finance represents number of anomalies that can be explained by market efficiency theory. Also, Malkiel (2003) noted that market participants can be indeed less rational, what can lead to presence of the predictable patterns in stock prices that can be persistent in short-term. He concluded that markets cannot be perfectly efficient, otherwise there would be no incentive for investors to investigate possible ways to outperform it, but in general, markets are remarkably efficient with respect to the utilization of information.

Fama (1970) categorized market efficiency by types of information that is reflected in the stock prices and by speed of prices' adjustment to new information. According to Fama (1970) there are three forms of market efficiency, namely weak, semi-strong and strong forms.

- *The weak form of market efficiency:*

The weak form of market efficiency implies that the information incorporated in the historical prices (e.g. dividends, trading volumes) is reflected in the current prices. This implies that only current news, which can be either positive or negative with no systematic pattern, provoke decline and increase in prices. When market exhibits weak form efficiency it is impossible to earn abnormal returns from technical analysis based on historical price movements. So that it implies that there can be no predictable pattern in the historical prices, and rates of return are independent of each other. The independence of the rates of return and random and unpredictable behavior of prices are the factors that indicate the weak form market efficiency.

The Efficient Market Hypothesis in its weak form has relevance to a Random Walk Hypothesis. The Random Walk Hypothesis states that stock prices follow a random walk process and it is impossible to predict future price changes analyzing the historical price movements.

- *The semi-strong form of market efficiency:*

The semi-strong form of market efficiency states that all publicly available information (e.g. financial statements, announcements) is accounted in the stock prices and neither technical analysis nor fundamental analysis, which is based on the publicly available information, can be utilized to predict future price movements or determine mispriced stock. Note that semi-strong form of market efficiency incorporates weak form efficiency, since all historical information is publicly available.

Semi-strong form of market efficiency also relates to the speed of adjustment of prices to the new publicly available information, it is considered that the prices adjust immediately.

- *Strong form of market efficiency:*

The strong form of market efficiency states that all information, public or private, is reflected in the stock prices. That is, if one has an inside information (e.g. information about magnitude of future earnings) and can apply it on trading, he will not be able to earn abnormal returns, since all information is already reflected in stock prices.

Strong form of market efficiency comprises weak and semi-strong efficiency forms.

## 2.4 Random Walk Hypothesis

A Random Walk Hypothesis (RWH) relates to the hypothesis testing that stock prices follow a random walk process. The random walk theory attained the popularity since Malkiel issued a book in 1973 “*A Random Walk Down Wall Street*”, where he emphasized that stock prices exhibit a random walk and it is not possible to consistently outperform the market. Also, Malkiel (2003) noted that since information is immediately reflected in stock prices, today’s price changes reflect today news and tomorrow’s price changes reflect tomorrow news, so that they are independent of each other, and due to the unpredictability of the news, price changes are random.

The RWH implies that stock price changes have the same distribution, are independent of each other and evolve according to a random walk, so that it is impossible to predict successive price changes analyzing historical price movements or any other past information. In particular, in the random walk model, prediction of the future variable’s values does not provide useful information because future values can equally likely be higher or lower compared to the last observed value. Fama (1965) indicated that randomness and independence of price changes are consistent with the concept for market efficiency. Thereby, the random and unpredictable from the past information price behavior, which is common for the random walk process, can be attributed to the weak form efficiency.

The random walk model with drift is represented by:

$$X_t = \alpha + X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2)$$

where,  $X_{t-1}$  is lag of the dependent variable,  $\alpha$  is a drift term, and the coefficient of  $X_{t-1}$  equals unity.

A drift term is included in the model if mean of the dependent variable is non zero, if the mean equals zero, the drift term should be excluded from the model. A random walk without drift represents a purely random process that takes a random step away from its last observed value. A random walk with drift, that is, a model that includes constant term, suggests that values are randomly drifting.

A random walk process relates to a non-stationary process which is the opposite to a stationary, mean-reverting process. Commonly transforming non-stationary series into a first order difference, that is,  $X_t - X_{t-1}$ , provides stationarity. Such series is said to be integrated of order 1, I(1), or to have a unit root. In some cases, variables should be transformed several

times to obtain a stationary series, such series is considered to be integrated of order  $d$ ,  $I(d)$ , where  $d$  indicates a number of times the series should be transformed to get stationarity.

To apply a random walk model to stock prices, the dependent variable  $X_t$  can be replaced by the natural logarithm of stock price, so that logarithmic stock prices following a random walk process can be written as:

$$\ln(P_t) = \alpha + \ln(P_{t-1}) + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2)$$

where  $P_t$  stands for stock price at time  $t$ .

Then, the first order difference of the logarithmic prices is a logarithmic return on the stock:

$$r_t \equiv \ln\left(\frac{P_t}{P_{t-1}}\right) = \alpha + \varepsilon_t$$

In this application, the logarithmic returns,  $r_t$ , are increments that are independent and identically distributed with mean  $\alpha$ .

## Calculation of returns

In the previous section the logarithmic returns were used as increments of logarithmic prices. Here, some advantages of using logarithmic returns over linear returns are provided.

Linear returns are found by following formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

And logarithmic returns are represented by logarithmic price changes:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

Logarithmic returns are approximation of linear returns when returns are small:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \cong \frac{P_t}{P_{t-1}} - 1$$

The log returns are preferred over linear returns primary due to ease of calculation, since they are given by the first order difference of the logarithmic prices. Also, logarithmic returns exhibit a time-additivity property, which is useful if we assume a normal distribution of the logarithmic returns.

### **3 Market Inefficiency anomalies**

Anomalies relate to a kind of distortions that contradict the efficient market theory. Thereby, presence of market anomalies provides results that deviate from the market efficiency theory and creates opportunity to earn abnormal returns. There are different categories of market inefficiency anomalies distinguished in research, in particular fundamental, technical and calendar anomalies.

Technical anomalies relate to the idea that it is possible to predict future price changes analyzing past information. A common example of a technical analysis technique is moving average or momentum, the latter suggests application of the contrarian strategy to earn abnormal returns. When an anomaly is present on the market, technical analysis helps to generate a technical trading rule to beat the market.

Fundamental anomalies relate to the stock price valuation anomaly. One of the examples of the fundamental anomalies is an anomaly connected to the book-to-market ratio. It was found in much research that companies with low book to market ratios within a certain period outperform the ones with high ratio. This relates to the fact that stock values of well-known companies are overestimated, while stock values of less known companies are underestimated.

Calendar anomalies relate to the observation that the distribution of returns on stock is unequal for a certain calendar period. One example of the calendar anomaly is the Weekend effect, when returns on an index are systematically higher on Friday and lower on Monday.

Further, we will study more about calendar anomalies, in particular Weekend, Turn-of-the-month, Intra-month, Turn-of-the-year and Holiday effects.

#### **3.1 Calendar effects**

Calendar effects imply that at a particular day, month or period of the year stock returns behave contrary to the market efficiency hypothesis. The anomaly is reflected in the varying distribution of returns on stocks within the investigated period, and this variation may present a systematic pattern. Thereby, presence of calendar effects can entail emergence of a predictable pattern in returns that can be utilized by investors to earn abnormal returns. There were several calendar effects described in the literature, which were found to be present in many stock markets. To such calendar anomalies can be attributed the following effects:

- *Day-of-the-week effect/ Weekend effect*

The day-of-the-week effect relates to the significant inequality in mean of returns for different days of the week. In particular, it was found that returns on Monday are on average the smallest and sometimes even negative, while returns on Friday are positive and highest compared to returns on other days of the week. This anomaly is also known as the weekend effect.

Cross (1973) was one of the first who documented that returns exhibit non-randomness when he observed returns distributions for different days of the week. Primary, he noticed a difference in the returns distribution on Monday and Friday, where on Monday returns were negative and on Friday high and positive. Furthermore, French (1980) found persistent negative returns on Monday, that refers to market inefficiency. He called the observed effect the “Weekend effect”. As a possible explanation of the effect, he suggested that firms tend to announce negative news on weekends to avoid massive stock sales caused by panic. Miller (1988) suggested that the weekend effect is a result of individual investor trading patterns. Individual investors are mostly recommended by brokerage community to take a buy decision during the week, while on the weekend they have more time to revise their portfolios and take a sell decision on Monday. Kamara (1997) observed that the weekend effect is persistent in small cap stocks compared to large cap stocks. Much other research also reported presence of the weekend effect in stock markets (Rogalski (1984), Agrawal and Tandon (1994) and others).

- *Turn-of-the-month and intra-month effects*

The turn-of-the-month effect relates to the pattern of stock prices to rise on the last trading day in the month and the first few trading days of the following month, while the intra-month effect relates to unequal distribution of returns within a month, in particular, high positive returns at the first half of the month, comparing to the second half.

Ariel (1987) was first who reported that returns tend to be higher on the last days and the first half of the month. Lakonishok and Smidt (1988) showed that US stock market returns are higher on the last trading day in the month and first 3 trading days of the following month, compared to the rest of the month. Many other researchers also documented presence of the turn-of-the-month effect in stock markets, in particular Cadsby and Ratner (1992), McConell and Xu (2008), Hensel, Sick and Ziemba (1994) and others. Dzhavarov and Ziemba (2010)

found that the turn-of-the-month effect still exists in the market, but due to its anticipation, days of occurrence changed.

It was suggested as possible explanation of the turn-of-the-month effect that cash flows received by pensioners from pension fund at the end of the month are reinvested into the stock market, that causes prices to rise. Nikkinen et al (2007) suggested that the U.S. macroeconomic news announcement can partially explain the turn-of-the-month effect.

- *Turn-of-the-year effect/ January effect*

The turn-of-the-year effect relates to the seasonal pattern in the stock market associated with increasing trading volumes and higher stock prices at the last week of December and first two weeks of January. Rozeff and Kinney (1976) observed that January returns on an equally-weighted NYSE index were seven times higher in comparison to returns on other months. Keim (1983) found that the effect relates to the observation that the small cap stocks outperform large cap stocks, so the effect is a small capitalization phenomenon, which was also confirmed by Roll (1983).

The described phenomenon has been under investigation during recent years. The explanation to the anomaly was proposed to be a tax-loss selling hypothesis that suggests that at the end of December investors sell stocks that give them losses to lower tax on capital gain. Next month, that is, in January, they reinvest their profit from sales in the market, stimulating prices to rise. The tax loss selling hypothesis was tested in several stock markets and was shown to be an appropriate explanation in many of them. However, there was debate over its sufficiency. For instance, Jones, Pearce and Wilson (1987) checked existence of the January effect in the U.S. stock market and found presence of the anomaly prior to introduction of the income tax.

- *Holiday effect*

The holiday effect is expressed by a tendency for stock returns to exceed the normal value at the last trading day before holiday comparing to the observations on the rest of the year. Lakonishok and Smidt (1988) found returns on the U.S. pre-holiday period to be enormously larger than returns on other days. They reported that returns on pre-holiday days are larger than returns at the end of the week. Other studies provide similar results (Ariel (1990), Kim and Park (1994), etc.)



## 4 Methods and data

### 4.1 The Data

The data used to analyze the Oslo Stock Exchange is daily closing prices on the OBX, OSEAX and OSESX indices. Indices are traded on weekdays from Monday to Friday. OSEAX is Oslo Børs All Share index, it consists of all shares traded at the Oslo Børs. The index is adjusted to corporate actions daily and reflects the current outstanding number of shares. OBX index consists of 25 the most traded securities based on the six month turnover rating, it is a semiannually revised index. The total weighting of non-EEA companies in OBX index cannot exceed a 10% limit. OSESX is the Oslo Børs Small Cap Index that consists of the 10% lowest capitalized shares on Oslo Børs, it is semiannually revised. All mentioned indices are adjusted for dividends payments. [1] The data for all three indices has a time range of 03.01.2000-30.12.2014. There are 3764 observations of the daily closing prices per each index.

The historical closing prices on OSEAX and OSESX indices were collected from the statistics section on the webpage of the Oslo Børs [1]. The historical closing prices on OBX index were obtained from the website of the Finanzen.net GmbH. [2]

#### 4.1.1 Descriptive statistics

Before analyzing descriptive statistics for the log returns on the OSE indices, it is relevant to observe time series plots for the closing prices and log returns series. Plot 1 presents series on the closing prices on the OBX, OSEAX, OSESX indices. It can be observed that at some points in time prices on indices move slowly, whereas at others they move faster. This relates to the news announced within particular time period, namely, positive news conduce prices to grow, negative to decline. From plot 1 we can also notice visible price growth before the crisis 2008 and drop in the closing prices during the crisis (2008-2009). Also, it is evident that closing prices on the small cap index grew faster than closing prices on the OBX and OSEAX indices during the pre-crisis period and after the crisis occurred, until the last years when the magnitude of closing prices on small cap index became similar to the magnitude of closing prices on the OSEAX index.

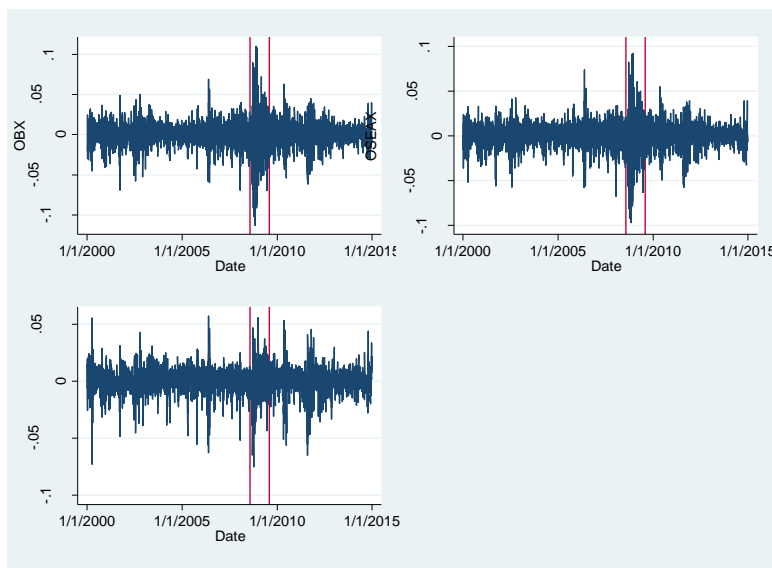
*Plot 1. Price series of closing prices on the OSE indices.*



Time series plot of closing prices on the OBX, OSEAX, OSESX indices for the time period January 2000 - December 2014.

Plot 2 presents time series for logarithmic returns on the OSE indices with emphasized period of high volatility that refers to the crisis 2008-2009 that was seen as a rapid drop of the closing prices on the OSE indices on the plot 1. From the plot 2 it is evident that disturbances are heteroskedastic with non-constant variance. Furthermore, there are periods of high and low volatility, when returns are respectively more or less dispersed, which indicate presence of volatility clustering in series.

*Plot 2. Time series plot of returns on the OSE indices.*



Time series plot for the returns on the OSEAX, OBX and OSESX indices for the time period January 2000-December 2014. The overlaid red lines determine crisis period that was accompanied with higher than normal volatility of returns. For the data on the OSE indices the highly volatile period indicates the time range 01.08.2008-31.07.2009.

Descriptive statistics of returns on the OSE indices are presented in the table 2. The skewness and kurtosis of empirical distributions for the OBX, OSEAX and OSESX indices deviate from theoretical normal distribution parameters which have skewness equal to 0 and kurtosis equal to 3. The skewness parameter indicates the asymmetry of the returns distribution around its mean, and kurtosis is a measure of the peakedness of the distribution.

For our data the skewness is negative which means that the distribution is skewed to the left, so that the distribution is more overspread towards negative values. In terms of the financial returns data it means that there is a significant probability of small gains and a small probability of large losses in terms of obtaining large negative returns. Also, we observe that the parameter of kurtosis is significantly different from 3. Positive excess kurtosis means that the distribution is peaked and is fat-tailed relative to the normal distribution. Such a distribution is usually called leptokurtic. Also, obtained test results of Shapiro-Wilk and Jarque-Bera normality tests suggest that the null hypothesis of normality of returns should be rejected at 5% significance level.

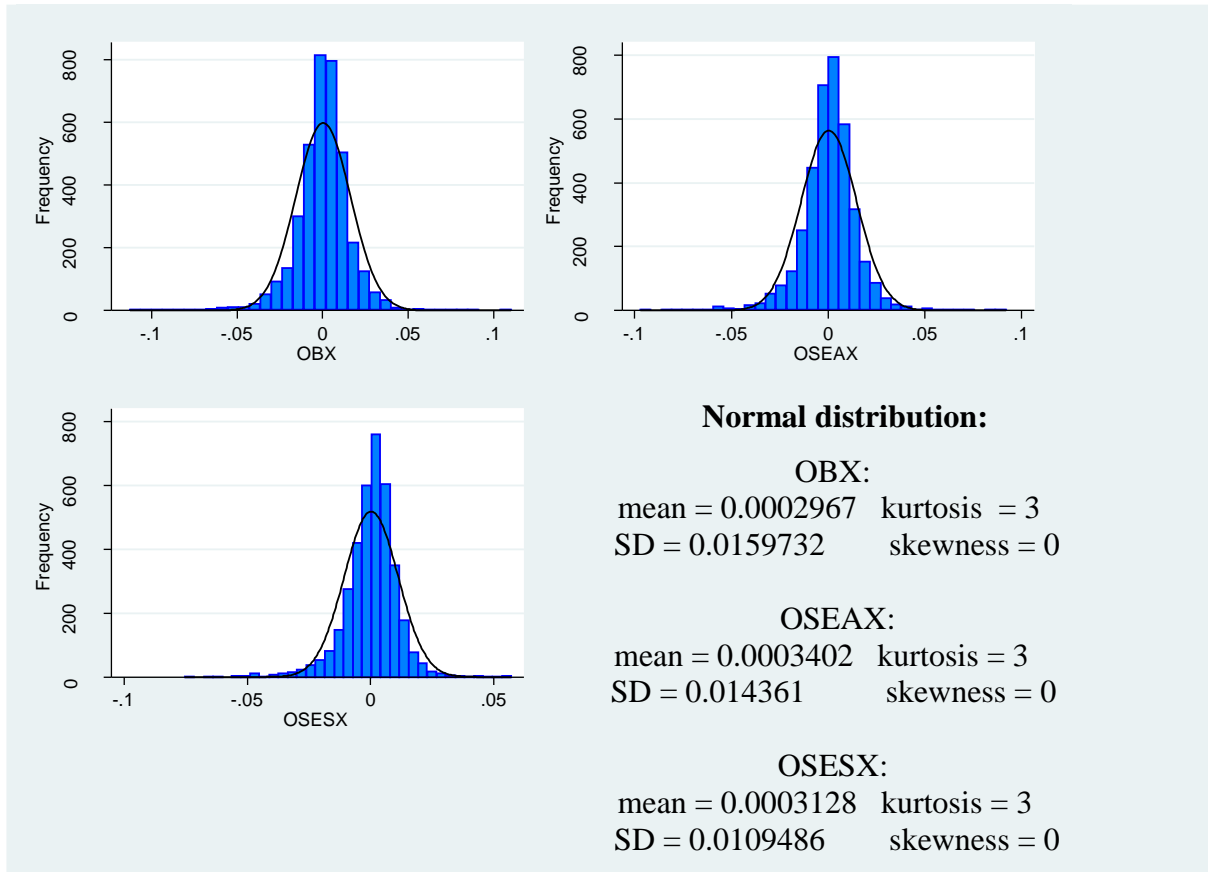
*Table 2. Descriptive statistics of the returns on the OBX, OSEAX and OSESX indices*

	OBX	OSEAX	OSESX
<i>Descriptive statistics</i>			
Mean, %	0.02967	0.03402	0.03128
Standard deviation	0.01597	0.01436	0.01095
Kurtosis	9.55755	9.09141	8.50847
Skewness	-0.54848	-0.61530	-0.90155
Minimum	-0.11273	-0.09709	-0.07525
Maximum	0.11020	0.09186	0.05718
No. of observations	3761	3761	3761
<i>Normality tests</i>			
JB normality test			
test statistics	6880	5992	5203
(p-value)	(0.000)	(0.000)	(0.000)
Shapiro-Wilk test			
test statistics	13.170	13.062	13.172
(p-value)	(0.000)	(0.000)	(0.000)
ARCH LM test	270.583	259.763	200.502
	(0.000)	(0.000)	(0.000)

Descriptive statistics of the returns on the OBX, OSEAX, OSESX indices for the time period January 2000-December 2014. Test results are represented by test statistics and p-value in the brackets.

Plot 3 presents the empirical distribution of the returns on OSE indices with overlaid normal distribution with means and variances of empirical distributions.

*Plot 3. Empirical distribution of returns on the OBX, OSEAX and OSESX indices with overlaid normal distribution.*



The empirical distribution for returns on each index is described by mean, standard deviation, kurtosis and skewness parameters that can be found in the table 2. The overlaid normal distribution exhibits the same mean and standard deviation values as the empirical distribution and for all cases kurtosis and skewness parameters of the normal distribution are 3 and 0 respectively.

From test results in this section, we can conclude that returns on the considered OSE indices exhibit heteroskedasticity with volatility clustering, what can be regarded as a typical property of financial data and in particular of stock returns series. Furthermore, returns on the OSE indices are not normally distributed, what is confirmed both by test statistics and by plot 3. The empirical distribution of returns is leptokurtic, which is characterized by large positive value of kurtosis parameter.

## 4.2 Methodology

As it was mentioned in the previous sections, weak form of market efficiency has a relevance to the Random Walk Hypothesis, which mainly indicates that returns are independent and unpredictable. Thus, testing the random walk hypothesis provides evidence towards weak form of market efficiency. In particular, if test results support the RWH for the series, it provides evidence of unpredictability of returns through use of historical information, since in the random walk model prediction does not provide any useful information. To test the weak form of market efficiency three tests are applied, namely the Variance Ratio test, the Phillips-Perron's unit root test and the Cumby-Huizinga autocorrelation test. The description of the tests is discussed in the following sections.

To detect calendar anomalies for returns on the OSE indices, an EGARCH(1,1)-t model is utilized. EGARCH model relates to the ARCH-type models, which are commonly used to model financial data. ARCH-type models account for heteroskedasticity and volatility clustering, which were found to be present in the data for returns on the OSE indices. To check robustness of the results, regression with application of the bootstrap procedure is applied. Sullivan, Timmermann and White (1998) suggested that application of the same data to formulate and test hypotheses leads to data snooping bias, thereby the authors suggested application of the bootstrap procedure to account for the bias. Additionally, non-parametric Kruskal-Wallis test is computed. Returns are divided into the groups and under a null hypothesis of the Kruskal-Wallis test all groups come from the same population, allowing us to test the equality of distribution of returns within a particular calendar period. The mentioned methodologies are adopted from the works on the calendar effects of Borges (2009), Szakmary and Kiefer (2004) and Nikkinen et al (2007). More detailed description of methodology is provided further.

### 4.2.1 Random Walk Hypothesis testing

#### Cumby-Huizinga autocorrelation test

The Cumby-Huizinga autocorrelation test was proposed by Cumby and Huizinga (1992). The advantage of the test is that it accounts for conditional heteroskedasticity in the error process. Moreover, the test is more flexible in a null hypothesis specification. There are two null hypotheses tested:

$H_0^1$ : disturbance is serially uncorrelated

$H_0^2$ : disturbance is MA(q) process up to order  $q = (\text{lag} - 1)$

Under the first null hypothesis, there are no serial correlation in disturbance, whereas the second null hypothesis states that serial correlation exists, but it dies out at some finite lag.

When disturbance is assumed to be homoskedastic, the test statistics of the Cumby-Huizinga test is identical to the Breusch-Godfrey autocorrelation test. As it was mentioned by Baum, Schaffer and Stillman (2007) Cumby Huizinga autocorrelation test is generalization of Sargan's test for serial independence of regression errors, which in turns generalizes test proposed by Breusch and Godfrey.

### Variance ratio test

The Variance ratio test was introduced by Lo and MacKinlay (1988), testing an hypothesis of log price series following a random walk process with drift. With application of the variance ratio test Lo and MacKinlay (1988) rejected the null hypothesis of weekly index returns on the U.S. stock market following random walk, mainly due to presence of serial correlation in returns. The authors did not conclude upon market inefficiency, they suggested that there should exist a tool explaining correlation in returns.

Consider a random walk model of the logarithmic prices:

$$\ln(P_t) = \alpha + \ln(P_{t-1}) + \varepsilon_t, \quad \varepsilon_t \sim IID(0, \sigma^2)$$

If  $\ln(P_t)$  follow a random walk, then the variance of its increments,  $\ln(P_t) - \ln(P_{t-1})$ , is assumed to be linear. So that the variance of  $\ln(P_t) - \ln(P_{t-2})$  is twice variance of  $\ln(P_t) - \ln(P_{t-1})$ . The Variance Ratio test checks the validity of the assumption that linear relationship between variances of increments, that is, logarithmic returns, holds. The variance ratio should be unity for all observed time interval N:

$$VR(N) = \frac{V(N)}{NV(1)} = 1$$

Here,  $V(N)$  stands for the variance of returns observed within N periods and  $V(1)$  is variance of returns observed at first period.

If RWH is false, then N-periods variance ratio is given by formula:

$$VR(N) = 1 + \frac{2}{N} \sum_{\tau=1}^{N-1} (N - \tau) \rho_{\tau} \quad (1)$$

where  $\rho_{\tau}$  is correlation coefficient.

Under the null hypothesis, the variance ratio should be unity which implies uncorrelated returns with  $\rho_\tau=0$ . If the null hypothesis is rejected, then the variance ratio equals to 1 plus correlation term.

Lo and MacKinlay's Variance Ratio test statistic is robust to heteroskedasticity problem, non-normality of increments and ARCH processes, but it is sensitive to correlated price changes.

## Unit root test

To test the hypothesis that the variable follows a random walk process, or alternatively, that it has a unit root, the Phillips-Perron unit root test is utilized. The test was proposed by Phillips and Perron (1988) where they modified Dickey-Fuller test statistics by obtaining Newey-West standard errors, accounting for unspecified serial correlation and heteroskedasticity in disturbances. In the Dickey-Fuller statistic serial correlation was accounted by including additional lags into the model.

Phillips-Perron's test involves fitting the following model:

$$y_t = \alpha + \rho y_{t-1} + \delta t + u_t \quad (2)$$

where  $t$  is a trend,  $y_{t-1}$  lag of the dependent variable,  $u_t$  are independent and identically distributed with zero mean. To obtain estimates the OLS procedure is used.

The model can be reformulated in terms of logarithmic stock prices:

$$\ln(P_t) = \alpha + \rho \ln(P_{t-1}) + \delta t + u_t$$

Two approaches are tested:

- 1) Including trend and drift term in the model ( $\alpha \neq 0$  and  $\delta \neq 0$ );
- 2) Including only drift term in the model ( $\alpha \neq 0$  and  $\delta = 0$ ).

In both cases hypotheses that are tested are represented by:

$$H_0: \rho = 1 \text{ against } H_a: \rho < 1$$

Under the null hypothesis the time series is integrated of order 1, that is, the variable has a unit root. The alternative hypothesis states that the variable was generated by a stationary process.

## 4.2.2 Calendar anomalies

Among all studied research, that investigates presence of the calendar anomalies in stock markets, methodologies from one of the most recent works are adopted to detect presence of calendar effects at the Oslo Stock Exchange. The recent works in this field account for the shortcomings of previous works and utilize currently available information to solve the problem. The methodologies suggested by Borges (2009), Szakmary and Kiefer (2004) and Nikkinen et al (2007) are adopted with some minor modifications. Borges (2009) investigated presence of the day-of-the-week and month-of-the-year effects, the latter has relevance to the January effect. Szakmary and Kiefer (2004) investigated presence of the turn-of-the-year effect and Nikkinen et al (2007) investigated presence of the turn-of-the-month and intra-month effects and its possible explanation by U.S. macroeconomic news announcement utilizing approaches of Szakmary and Kiefer (2004) and Ariel (1987). All methodologies applied by these authors detect presence of calendar effects with application of ARCH-type models. Additionally Borges (2009) proposed to verify the result with estimation of regression with application of the bootstrap procedure. The bootstrap procedure was found to be relevant in calendar anomalies testing since it accounts for the data snooping bias (Cooper, McConnell and Ovtchinnikov (2006), Sullivan, Timmermann and White (1998)). Also, Borges (2009) applied the non-parametric Kruskal-Wallis rank test of equality among the groups to test equality of distribution of returns within a particular calendar period and checked the stability of the results with application of the rolling window regression.

### Kruskal Wallis rank test

This is a non-parametric test introduced by Kruskal and Wallis (1952). The null hypothesis states that there is no difference among samples from considered groups, against the alternative hypothesis that there is a difference among samples. The tested data is organized in the rank order from 1 to N regardless to which group each value belongs, with number 1 assigned to the smallest value and N to the largest.

The test statistics when there are no tied values is:

$$H = \frac{12}{N(N+1)} \sum_{j=1}^m \frac{R_j^2}{n_j} - 3(n+1)$$



Here,  $R_j$  is the sum of the ranks of the  $j$  group,  $m$  is the number of groups,  $n_j$  is the size of the  $j$  group and  $N$  is the total sample size.

The sampling distribution of the test statistics is approximately chi squared with  $m-1$  degrees of freedom, that is,  $H \sim \chi^2_{m-1}$ . [3]

## Model selection

From the section 4.1.1 we concluded that returns on the OBX, OSEAX and OSESX indices are not normally distributed, exhibit heteroskedasticity and tend to volatility clustering. Moreover, in table 2 the results of the Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (ARCH LM) test indicate that the null hypothesis of no ARCH effect can be rejected at 5% significance level for all three indices. These results imply that ARCH-type models, that account for ARCH component in the series, are the most convenient for modeling returns on the OSE indices.

The ARCH model was introduced by Engle (1982) who won a Nobel Prize in 2003 for this innovation. After the first ARCH model was introduced there were several extensions of the model proposed. The first is the Generalized ARCH (GARCH) model proposed by Bollerslev (1986), Exponential GARCH (EGARCH) model by Nelson (1991), Asymmetric Power ARCH (APARCH) by Ding, Granger and Engle (1993) and many others that are listed in the glossary written by Bollerslev (2008). Extensions of ARCH models, that are proposed to account for specific property of financial data, may nest other ARCH-type models. For instance, APARCH model nests seven ARCH-type models, including ARCH, GARCH, GJR, TARARCH and others.

Among ARCH-type models in Stata 13, two models showed the smallest parameters of AIC and BIC information criteria and the largest maximum likelihood values, namely the EGARCH(1,1)-t model and the APARCH(1,1)-t model, where “t” indicates t-distribution. The information criteria parameters for the two mentioned models are presented in the table 3 for the pre-crisis period, January 2000- July 2008, with 2153 observations.

According to the AIC and BIC information criteria, EGARCH(1,1)-t model should be chosen to model the OBX index returns, but the largest maximum likelihood is obtained the estimating APARCH(1,1)-t model. Based on the AIC information criterion and estimated value of maximum likelihood, the EGARCH(1,1)-t model should be selected to model returns on the OSEAX and OSESX indices. Contrary to that result the BIC information criterion suggests to choose the APARCH(1,1)-t model for the same indices' returns. So that, it is not

apparent which model should be selected to model returns on the OSE indices for the pre-crisis period (January 2000- July 2008).

*Table 3. Information criteria for ARCH-type models for the pre-crisis period*

<b>APARCH(1,1)-t</b>	<b>AIC</b>	<b>BIC</b>	<b>Maximum Likelihood</b>
OBX	-12848.51	-12786.09	<b>6435.253</b>
OSEAX	<b>-13198.53</b>	-13136.11	<b>6610.263</b>
OSSEX	<b>-14234.24</b>	-14120.83	<b>7137.118</b>
<b>EGARCH(1,1)-t</b>	<b>AIC</b>	<b>BIC</b>	<b>Maximum Likelihood</b>
OBX	<b>-12849.28</b>	<b>-12792.54</b>	6434.341
OSEAX	-13198.05	<b>-13141.31</b>	6609.027
OSSEX	-14227.28	<b>-14120.93</b>	7134.834

Bold numbers indicate the smallest information criteria and the largest maximum likelihood, respective to a column.

For the post-crisis period, August 2009-December 2014, there are 1360 observations. The application of the APARCH model for the post-crisis period is not possible due to too small sample size. As Danielsson (2011) suggested, when the sample size is too short, the calculation of estimates by numerical maximization of likelihood function is problematic for the APARCH model. But it is feasible for other ARCH-type models, such as e.g. the EGARCH model. Due to the described problem, the EGARCH(1,1)-t model was selected to model returns on the OSE indices for both periods.

Nelson's (1991) EGARCH model accounts for the asymmetric information property and the leverage effect. These are properties that are typically found in financial data such as stock prices. All ARCH-type models include mean and conditional variance equations. The EGARCH(1,1) model specification is introduced below.

Mean equation:

$$y_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1)$$

Conditional variance equation:

$$\ln \text{Var}(\varepsilon_t) = \ln(\sigma_t^2) = \alpha_0 + \gamma_1 z_{t-1} + \varsigma_1 (|z_{t-1}| - E|z_{t-1}|) + \gamma_2 \ln \sigma_{t-1}^2$$

where  $z_t = \frac{\varepsilon_t}{\sigma_t}$  is standardized innovations.

Here,  $\alpha_0$  is a constant term,

$\ln \sigma_{t-1}^2$  is a lag of the conditional variance,

$\varsigma_1$  measures the magnitude effect or a symmetric effect,  
 $\gamma_1$  captures asymmetric or leverage effect.

### Day-of-the-week effect testing

The methodology for the day-of-the-week effect testing is adopted from Borges (2009). To test the day-of-the-week (DOW) effect, that returns on the OSE indices differ for different weekdays, the following models are estimated:

➤ OLS estimation of regression using bootstrap procedure:

$$r_t = const + \beta_i DOW_{i,t} + \varepsilon_t \quad (3)$$

where  $r_t$  stands for returns on OSE index,  $DOW_{i,t}$  is the day-of-the-week dummy, that equals to 1 when returns are observed on  $i$ 's day of the week. Subscript  $i$  takes values of 1, 2, 3, 4, 5, that stands for Monday, Tuesday, Wednesday, Thursday and Friday respectively.

There are five regression equations estimated separately for each day of the week. Estimating each dummy individually allows us to capture the significance of returns on each day compared to returns on the rest of the week.

For returns on the OSE indices the bootstrap procedure is applied to the regression to obtain bootstrapped standard errors. Bootstrapping is a nonparametric approach that relies on random sampling with replacements from the original data and therefore it calculates sample parameters from empirical distribution. Also, application of the bootstrap procedure helps to cope with data mining problem (Cooper et al, 2006). A bootstrap procedure is applied to other calendar effect testing as well, in particular, turn-of-the-month, turn-of-the-year and holiday effects, but to avoid burdensome tables only significant results are mentioned.

➤ EGARCH(1,1)-t model:

Mean equation:

$$r_t = const + \beta_i DOW_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (4)$$

Conditional variance equation:

$$\ln \text{Var}(\varepsilon_t) = \ln(\sigma_t^2) = \alpha_0 + \gamma_1 z_{t-1} + \varsigma_1 (|z_{t-1}| - E|z_{t-1}|) + \gamma_2 \ln \sigma_{t-1}^2$$

where  $r_{t-i}$  are lags of returns on index. The lags are included in the model based on the autocorrelation test results, which are provided in the following section in the table 4. For the returns on the indices with serially uncorrelated disturbances, there are no lags included in

the model. For the returns on the indices with disturbances exhibiting serial correlation, the number of lags up to the significant results is included in the model, to account for serial correlation in returns. The same decision regarding inclusion of lags in the model holds for all following estimated models that are considered to detect presence of other calendar effects.

### Turn-of-the-month effect testing

A methodology for the turn-of-the-month effect testing is adopted from Nikkinen et al (2007) and Szakmary and Kiefer (2004). To test the presence of the turn-of-the month effect (TOM) at OSE, the following model is estimated:

➤ EGARCH(1,1)-t model, mean equation:

$$r_t = \sum_{i=-7}^{81} \alpha_i TOM_{i,t} + \alpha_0 ROM_t + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \sum_{i=1}^k \beta_i DOW_{i,t} + \varepsilon_t \quad (5)$$

Here,  $TOM_{i,t}$  are turn-of-the-month dummy variables of the 7 last trading days in the month and first 8 trading days of the following month, that is, a window of (-7, -6, ..., +7, +8) trading days. For instance,  $TOM_{+1,t}$  equals 1 when returns are observed on the first trading day in the month and 0 otherwise.  $ROM_t$  is rest of the month dummy variable that equals 0 when returns are observed within the window (-7, -6, ..., +7, +8) and equals 1 when returns are observed on other days in the month.  $DOW_{i,t}$  is day-of-the-week dummy, with index  $i = 1, 2, 3, 4, 5$  representing Monday, Tuesday, Wednesday, Thursday and Friday respectively. Only significant day-of-the-week dummy, based on the results in the table 7, will be included in the estimated model. It holds for all the following estimated models, namely for the models in the turn-of-the-year and holiday effects testing.

Additionally, the traditional TOM effect is estimated, that is indicated by 4 trading days, namely last trading day of the month and first three trading days of the following month. The following mean equation in EGARCH(1,1)-t model is estimated:

$$r_t = const + \alpha_i TOM_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \sum_{i=1}^k \beta_i DOW_{i,t} + \varepsilon_t \quad (6)$$

where  $TOM_{i,t}$  stands for dummy variable for the traditional TOM effect, that equals 1 when returns are observed on four trading days in the month cumulatively, namely in the window (-1, +1, +2, +3), and 0 otherwise. The remaining specification of the variables is the same, as was described previously.

To detect presence of the intra-month effect, the following model is proposed:

$$r_t = \eta_1 FH_t + \eta_2 SH_t + \varepsilon_t \quad (7)$$

where  $FH_t$  is a dummy variable for the first half of the month, it equals 1 when returns are observed on the last trading day in the month and first 8 trading day of the following month, that is, with window of  $(-1, +1, \dots, +7, +8)$ , and 0 otherwise. It was found in much research, including Ariel (1987), that the returns are higher on the last trading day in the month and first 3 trading days of the following month. That is why the dummy for the first half of the month contains the last trading day of the month.  $SH_t$  is a dummy variable of the second half of the month, it equals 1 when returns are observed on the 10<sup>th</sup> up to 2<sup>d</sup> last trading days of the month, that is, with a window of  $(-10, -9, \dots, -3, -2)$ , and 0 otherwise.

### Turn-of-the-year/ January effect testing

A methodology for the turn-of-the-year effect is adopted from Szakmary and Kiefer (2004). To detect presence of the turn-of-the-year (TOY) effect at the OSE the following model is estimated

➤ EGARCH(1,1)-t model, mean:

$$r_t = const + \sum_{i=1}^k \beta_i DOW_{i,t} + \alpha_1 TOM_t + \sum_{i=-7}^8 b_i TD_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (8)$$

Here,  $TOM_t$  is the dummy for the traditional turn-of-the-month that takes value 1 when returns are observed on the last trading day in the month and first 3 trading days of the following month, that is, a window of  $(-1, +1, +2, +3)$ .  $TD_{i,t}$  represent dummies for 15 trading days in December and January with the window  $(-7, -6, \dots, +7, +8)$ , namely 7 last trading days in December and 8 first trading days in January. For instance,  $TD_{-1,t}$  equals 1 when returns are observed on the last trading day in December, and 0 otherwise. Decision upon inclusion of  $DOW_{i,t}$  dummy variables and number of lags  $r_{t-i}$ , was discussed before.

Also, traditional turn-of-the-year effect is estimated in the following mean equation of EGARCH(1,1)-t model:

$$r_t = const + \sum_{i=1}^k \beta_i DOW_{i,t} + \alpha_1 TOY_t + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (9)$$

where  $TOY_t$  is a traditional turn-of-the-year dummy that is represented by window of  $(-1, +1, \dots, +5)$  trading days, that is, the last trading day in December and the first five trading

days in January.  $TOY_t$  equals 1 when returns are observed cumulatively on the last trading day in December and the first five trading days in January and 0 otherwise.

## Holiday effect

Holiday effect relates to the tendency of returns on index to exceed the normal value at the last trading day before holiday. Thereby, the significance of returns on the OSE indices at last trading day prior to the public holiday should be tested.

Three holiday effects are tested to detect presence of the holiday effect in the OSE indices, in particular, Christmas holiday, Easter holiday and Norwegian Constitution day.

To detect presence of the holiday effects, the following models are estimated:

➤ EGARCH(1,1)-t model, mean equation:

$$a) \quad r_t = const + \sum_{i=1}^k \beta_i DOW_{i,t} + \alpha_i preChristmas_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (10)$$

$$b) \quad r_t = const + \sum_{i=1}^k \beta_i DOW_{i,t} + \alpha_i preEaster_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (11)$$

$$c) \quad r_t = const + \sum_{i=1}^k \beta_i DOW_{i,t} + \alpha_i preNConst_{i,t} + \sum_{i=1}^n \lambda_{t-i} r_{t-i} + \varepsilon_t \quad (12)$$

where  $preChristmas_{i,t}$ ,  $preEaster_{i,t}$ ,  $preNConst_{i,t}$  are dummy variables for the last trading day prior to Christmas, Easter and Norwegian Constitution day respectively. Particularly, the  $preChristmas_{i,t}$  dummy takes value 1 when returns are observed on the last trading day before Christmas and 0 otherwise, the  $preEaster_{i,t}$  dummy takes value 1 when returns are observed on the last trading day before Easter and 0 otherwise, and the  $preNConst_{i,t}$  dummy takes value 1 when returns are observed on the last trading day before Norwegian Constitution day and 0 otherwise. Inclusion of  $DOW_{i,t}$  dummy and lags of return was discussed previously.

# 5 Empirical results

## 5.1 Random walk hypothesis

### Autocorrelation test

Presence of serial correlation in disturbances of returns on the OSE indices is tested with application of the Cumby Huizinga autocorrelation test. Autocorrelation test results for the pre- and post-crisis periods are presented in table 4. The test is robust to heteroskedasticity and it tests two null hypotheses: disturbance is serially uncorrelated and disturbance is MA(q) process up to order  $q=(lag-1)$ .

Test results are introduced for 10 lag length and are skipped for the next 10 lags (from 11-20 lags) due to its insignificance, that is, test results support the hypothesis of serially uncorrelated residuals of the returns on the OBX and OSEAX indices and for the returns on the OSESX index the correlation dies out before 10<sup>th</sup> lag for both periods.

Test results provide no evidence of serially correlated residuals of returns on the OBX and OSEAX indices for any of the two time periods, but there is strong evidence of serial correlation in the returns on the OSESX index. For the pre-crisis period, at 5% significance level there is evidence of correlation in returns on the small cap index up to 9<sup>th</sup> lag, but the correlation coefficients are largest for 2<sup>d</sup> and 4<sup>th</sup> lags. Indeed, when the residuals are obtained from the model where OSESX index returns are regressed on the first 4 lags, test statistics of the Cumby-Huizinga test support the hypothesis of uncorrelated returns. For the post-crisis period, serial correlation in residuals of returns on the OSESX index dies out after 2<sup>d</sup> lag at 5% significance level.

Presence of serially correlated residuals of returns on the OSESX index can be induced by infrequent trading. Stocks of the companies listed on the OSESX index on average are traded not all trading days in the year, while stocks listed on the OBX index belong to the most traded and they are traded all trading days in the year when OSE is open. According to Lo and MacKinlay (1988), infrequent trading causes the information to not immediately being reflected into the price of the small stock. The information is impounded into the small stocks with a lag after it is reflected in the large stocks. This lag creates a positive serial correlation in the stock returns on the OSESX Small Cap index.

Table 4. The Cumby-Huizinga autocorrelation test results for returns on OSE indices

Pre-crisis period (January 2000-July 2008)									
Lag	OBX			OSEAX			OSESX		
	Correlation coefficient	$H_0^1$ : Uncorrelated	$H_0^2$ : Correlated up to finite lag	Correlation coefficient	$H_0^1$ : Uncorrelated	$H_0^2$ : Correlated up to finite lag	Correlation coefficient	$H_0^1$ : Uncorrelated	$H_0^2$ : Correlated up to finite lag
1	-0.0008	0.001 (0.9786)	0.001 (0.9786)	0.0026	0.007 (0.9341)	0.007 (0.9341)	0.0786	<b>4.540</b> <b>(0.0331)</b>	<b>4.540</b> <b>(0.0331)</b>
2	0.0153	0.264 (0.8764)	0.262 (0.6088)	0.0220	0.504 (0.7774)	0.549 (0.4588)	0.1143	<b>14.629</b> <b>(0.0007)</b>	<b>12.555</b> <b>(0.0004)</b>
3	0.0064	0.310 (0.9582)	0.050 (0.8223)	0.0033	0.508 (0.9171)	0.012 (0.9143)	0.0361	<b>14.819</b> <b>(0.0020)</b>	1.073 (0.3003)
4	0.0293	1.342 (0.8542)	0.934 (0.3339)	0.0447	2.788 (0.5940)	2.043 (0.1529)	0.1199	<b>23.102</b> <b>(0.0001)</b>	<b>12.579</b> <b>(0.0004)</b>
5	-0.0337	2.865 (0.7208)	1.758 (0.1848)	-0.0327	4.085 (0.5372)	1.512 (0.2188)	0.0084	<b>24.331</b> <b>(0.0002)</b>	0.084 (0.7726)
6	0.0174	3.259 (0.7757)	0.522 (0.4699)	0.0123	4.305 (0.6355)	0.270 (0.6031)	0.0039	<b>24.466</b> <b>(0.0004)</b>	0.020 (0.8888)
7	0.0079	3.315 (0.8544)	0.099 (0.7531)	0.0051	4.329 (0.7412)	0.046 (0.8304)	0.0533	<b>27.994</b> <b>(0.0002)</b>	<b>4.310</b> <b>(0.0379)</b>
8	0.0477	5.738 (0.6766)	2.727 (0.0987)	0.0494	6.849 (0.5530)	2.741 (0.0978)	0.0548	<b>30.166</b> <b>(0.0002)</b>	2.380 (0.1229)
9	0.0275	7.023 (0.6347)	1.273 (0.2592)	0.0410	9.173 (0.3742)	2.902 (0.0885)	0.0551	<b>32.241</b> <b>(0.0002)</b>	<b>5.251</b> <b>(0.0219)</b>
10	-0.0215	8.328 (0.5968)	0.637 (0.4249)	-0.0200	10.731 (0.3789)	0.522 (0.4701)	-0.0166	<b>34.312</b> <b>(0.0002)</b>	0.403 (0.5255)
Post-crisis period (August 2009-December 2014)									
Lag	OBX			OSEAX			OSESX		
	Correlation coefficient	$H_0$ : Uncorrelated	$H_0$ : Correlated up to finite lag	Correlation coefficient	$H_0$ : Uncorrelated	$H_0$ : Correlated up to finite lag	Correlation coefficient	$H_0$ : Uncorrelated	$H_0$ : Correlated up to finite lag
1	-0.0111	0.110 (0.7402)	0.110 (0.7402)	0.0030	0.008 (0.9303)	0.008 (0.9303)	0.1633	<b>14.011</b> <b>(0.0002)</b>	<b>14.011</b> <b>(0.0002)</b>
2	0.0273	0.654 (0.7212)	0.471 (0.4927)	0.0376	0.978 (0.6131)	0.874 (0.3500)	0.1265	<b>15.363</b> <b>(0.0005)</b>	<b>5.945</b> <b>(0.0148)</b>
3	-0.0594	3.327 (0.3439)	2.249 (0.1337)	-0.0579	3.893 (0.2732)	2.134 (0.1440)	-0.0049	<b>19.530</b> <b>(0.0002)</b>	0.012 (0.9119)
4	-0.0194	5.702 (0.2226)	2.239 (0.1345)	-0.0513	6.222 (0.1832)	2.392 (0.1220)	-0.0388	<b>21.478</b> <b>(0.0003)</b>	0.728 (0.3936)
5	-0.0387	6.151 (0.2918)	1.066 (0.3017)	-0.0410	6.603 (0.2519)	1.088 (0.2969)	-0.0479	<b>21.501</b> <b>(0.0007)</b>	1.167 (0.2799)
6	-0.0489	8.084 (0.2320)	2.687 (0.1012)	-0.0455	8.212 (0.2230)	2.272 (0.1317)	-0.0465	<b>21.990</b> <b>(0.0012)</b>	1.303 (0.2536)
7	0.0423	10.024 (0.1872)	0.986 (0.3208)	0.0351	9.856 (0.1969)	0.691 (0.4059)	0.0230	<b>22.773</b> <b>(0.0014)</b>	0.178 (0.6733)
8	-0.0675	13.300 (0.1019)	3.617 (0.0572)	-0.0612	12.899 (0.1154)	3.037 (0.0814)	-0.0263	<b>25.228</b> <b>(0.0014)</b>	0.803 (0.3701)
9	0.0155	13.300 (0.1495)	0.196 (0.6583)	0.0211	12.936 (0.1655)	0.354 (0.5517)	0.0350	<b>26.302</b> <b>(0.0018)</b>	0.609 (0.4353)
10	-0.0123	13.337 (0.2054)	0.171 (0.6795)	-0.0113	13.002 (0.2236)	0.129 (0.7200)	0.0193	<b>27.734</b> <b>(0.0020)</b>	0.293 (0.5880)

The table presents test results for the serial correlation in returns on the OBX, OSEAX and OSESX indices. The columns contain test statistics with p-value in the brackets. The bold figures emphasize test results that provide evidence to reject the null hypothesis at 5% significance level.



## Variance Ratio test

Variance ratio test results are presented in the table 5. Test results support the null hypothesis of log prices following a random walk process for logarithmic closing prices on the OBX index for both periods. The results for the log prices on the OSEAX index indicate some sort of inefficiency in the pre-crisis period, but overall efficiency improved in the post-crisis period.

*Table 5. The Overlapping Lo and MacKinlay's Variance Ratio test results*

	OBX	OSEAX	OSSESX
<b>Pre-crisis period (January 2000-July 2008)</b>			
<b>q=2</b>	0.998 (0.9567)	1.002 (0.9576)	1.078 (0.0346)**
<b>q=10</b>	1.106 (0.3007)	1.146 (0.1636)	1.655 (0.0000)***
<b>q=20</b>	1.221 (0.1249)	1.291 (0.0481)**	2.056 (0.0000)***
<b>q=40</b>	1.292 (0.1354)	1.407 (0.0410)**	2.612 (0.0000)***
<b>q=80</b>	1.388 (0.1380)	1.559 (0.0340)**	3.392 (0.0000)***
<b>Post-crisis period (August 2009-December2014)</b>			
<b>q=2</b>	0.992 (0.8030)	1.006 (0.8700)	1.166 (0.0001)***
<b>q=10</b>	0.813 (0.1212)	0.853 (0.2260)	1.370 (0.0109)**
<b>q=20</b>	0.741 (0.1398)	0.783 (0.2182)	1.478 (0.0177)**
<b>q=40</b>	0.616 (0.1206)	0.662 (0.1711)	1.527 (0.0501)*
<b>q=80</b>	0.687 (0.3615)	0.762 (0.4866)	2.169 (0.0013)***

The table presents the variance ratio test for the time periods determined by q, where q=2 is 2 days and q=80 is 80 days. The table contains robust to heteroskedasticity test statistics (variance ratios) given by equation (1) and p-value in the brackets. The tested null hypothesis is that the log prices on the indices follow a random walk process.

\* reject null hypothesis at 10% significance level

\*\* reject null hypothesis at 5% significance level

\*\*\* reject null hypothesis at 1% significance level

The Variance Ratio, given by the equation (1), of the logarithmic prices on the OSSESX index is significantly above 1, providing evidence to reject the hypothesis that prices follow a random walk process. From the test specification we know that the Variance Ratio test is sensitive to serial correlation in returns. When returns are correlated, the variance ratio will become unity plus a correlation term. As it was found from the results in table 4, returns on the OSSESX index exhibit positive correlation. This implies that we anticipate getting variance ratios equal to one plus some positive term, what is confirmed by results in the table 5.

From the test results we can conclude that in the pre-crisis period there was some evidence of non-random walk behavior of log prices on the OSEAX index, but after the crisis occurred, the distortion that existed in the market disappeared. For the OBX index, test results provide evidence of constancy in random walk behavior of prices. The RWH for the log prices on the OSESX index is still rejected at different significance levels, due to presence of positive serial correlation in the OSESX index returns. Here, we can note that the variance ratios became smaller for the post-crisis period as  $q$  increases, that is, for the pre-crisis period for  $q=80$  the variance ratio is 3.392, for the post crisis period it equals 2.169. It can probably be explained by shorter horizon of serial correlation in the post-crisis period, which is consistent with the autocorrelation test results in table 4, where serial correlation in OSESX index returns in the post-crisis period exists only up to second lag.

## Unit root test

Table 6 presents results of the unit root test for the log closing prices on the OBX, OSEAX and OSESX indices. The null hypothesis of the Phillips-Perron (PPerron) test states that there is presence of a unit root in each series, and the test procedure includes fitting the model given by equation (2). The test accounts for the serial correlation and heteroskedasticity problems by application of the Newey-West serial correlation robust standard errors.

*Table 6. The unit root tests of the log closing prices on the OSE indices*

	OBX	OSEAX	OSESX
<b>Pre-crisis period (January 2000-July 2008)</b>			
<b>PPerron (no trend)</b>	0.243 (0.9332)	0.007 (0.9591)	-0.056 (0.9537)
<b>PPerron (with trend)</b>	-1.611 (0.7880)	-1.678 (0.7606)	-1.611 (0.7880)
<b>Post-crisis (August 2009-December 2014)</b>			
<b>PPerron (no trend)</b>	-1.773 (0.3939)	-1.688 (0.4374)	-1.527 (0.5203)
<b>PPerron (with trend)</b>	-3.128 (0.0998)	-2.905 (0.1607)	-1.528 (0.8192)

Results in the table are represented by test statistics and p-value in parentheses.

The results of the Phillips-Perron unit root test provide evidence of price series for OBX, OSEAX and OSESX indices to have a unit root, in particular to follow a random walk process with a drift, at 5% significance level. The result is steady, it holds within two tested periods.

## Conclusion

In this section, test results for the RWH were introduced. The results provide support of the random walk hypothesis for the logarithmic closing prices on the OBX and OSEAX indices, with OSEAX index showing improving market efficiency. It implies that there is no evidence against weak form market efficiency of the part of the Oslo Stock Exchange represented by firms which stocks are listed on the OBX and OSEAX indices. Results for log closing prices on the OSESX index from the Variance ratio test suggest rejection of the hypothesis of stock prices following a random walk, but results for this test were affected by presence of serial correlation in OSESX index returns, which was detected by the Cumby-Huizinga autocorrelation test results in the table 4. Phillips-Perron's unit root test accounts for serial correlation in series, and the test results support the hypothesis of log stock prices on the OSESX index to have a unit root, that is, to follow a non-stationary process.

Serial correlation in returns per se is inconsistent with market efficiency. Presence of serial correlation makes stock prices predictable through use of historical information. Significant positive serial correlation in stock returns imply that if daily returns start to rise, the continuation of increase is anticipated for the next period. For returns on the small cap index, correlation is significant but too small to be used to generate excess returns, that is, the largest correlation coefficient from the table 4 is 0.1633. Furthermore, serial correlation in returns on the small cap index is diminishing, that is, in the pre-crisis period serial correlation died out after 9<sup>th</sup> lag, whereas in the post-crisis period serial correlation exists only up to 2<sup>d</sup> lag. So that, we cannot conclude upon inefficiency of the small cap index at the Oslo Stock Exchange, but probably this part of the market is less efficient due to some distortion that affect price formation process.

## 5.2 Calendar effects

### 5.2.1 Day-of-the-week effect

The results, obtained by estimation of equation (3) and equation (4), are presented in table 7. It is evident that there is a persistent day-of-the-week effect in returns on the OSESX index. For returns on the OBX and OSEAX indices the anomaly is short-term, it disappeared after the crisis.

Particularly, for the pre-crisis period there is evidence of the positive excess Friday and Thursday returns on the OBX and OSEAX indices. Returns on Thursday become insignificant when regression equations are estimated with application of a bootstrap procedure. The results are consistent with the findings of Sæbø (2008) who tested the DOW effect in returns on OSE indices for the 1990-2005 period and found positive excess returns on Friday and Thursday, but the Thursday effect was not robust. Also the pattern of the significantly positive returns on Friday for returns on the OSEAX index on 1994-2007 was found by Borges (2009). After the crisis occurred there is no DOW effect revealed in the OBX and OSEAX indices. One possible explanation is that the documented anomaly was traded out by investors on the market.

*Table 7. The estimated results for the day-of-the-week anomaly.*

	<i>EGARCH(1,1)-t</i>	<i>Regression (bootstrap.)</i>	<i>Kruskal-Wallis Test</i>
<b><i>Pre-crisis (January 2000-July 2008)</i></b>			
<b>OBX</b>	Thursday(+)**	-	6.883
	Friday(+)**		(0.1422)
<b>OSEAX</b>	Thursday(+)**	Friday(+)**	10.086
	Friday(+)**		(0.0390)**
<b>OSSESX</b>	Tuesday(-)**	Friday(+)**	27.123
	Friday(+)**		(0.0001)***
<b><i>Post-crisis (August 2009-December 2014)</i></b>			
<b>OBX</b>	-	-	0.720
			(0.9489)
<b>OSEAX</b>	-	-	1.373
			(0.8489)
<b>OSSESX</b>	Tuesday(-)**	Friday(+)**	10.946
	Friday(+)**		(0.0272)**

The signs in the brackets correspond to the sign of the coefficient in estimated model. The chi square test is applied to test linear restrictions of equality of returns on different days of the week.

\*\*\*significant at 1% significance level

\*\* significant at 5% significance level

For the OSSESX index, returns on Friday were found to be significantly positive, while returns on Tuesday significantly negative. But the Tuesday effect is not robust, since it disappeared when bootstrap procedure is applied. The pattern of the positive significant returns on Friday is persistent and Kruskal-Wallis test results confirm unequal distribution for

returns on the small cap index for both tested periods. This was also noticed by Hansen et al (2005), who tested the hypothesis of no calendar effects in returns on the OSEAX, OBX and OSESX indices for 1995-2002 period and found that the calendar effects diminish for the last years except in the small cap indices, including the OSESX index.

As it was suggested by Borges (2009), the stability of the Friday effect in the small cap index can be examined with application of the rolling window regression.

The regression equation has the following form:

$$r_t = const_t + \sum_{i=1}^4 \lambda_{t-i} r_{t-i} + \beta F_t + \varepsilon_t \quad (13)$$

where  $F_t$  is the dummy for the returns on Friday, that takes value 1 when returns are observed on Friday and 0 when returns are observed on other days of the week. Standard errors are calculated using the robust estimation, so that heteroskedasticity-consistent standard errors are obtained. The lags for the returns,  $r_{t-1}$ , are included to account for autocorrelation in returns on the OSESX index.

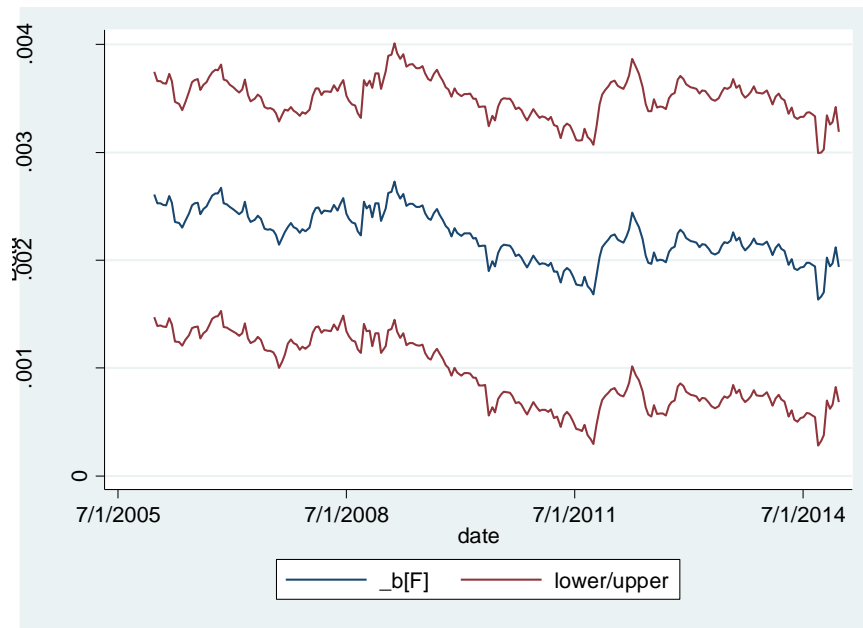
The rolling window regression implies estimation of the regression equation several times to obtain the estimated value of  $\beta$  that evolves over time.

Here, the rolling regression with window 1500 and step 10 is applied. Window 1500 implies that the regression is estimated from 1500 observations, approximately 6 years, and step 10 means that the observations are moved by 10 when repeating estimation of the regression equation. The first regression is estimated on [1:1500] observations and an estimate of  $\hat{\beta}$  and standard error are obtained. Then estimate regression for the [11:1510], again obtain  $\hat{\beta}$  and standard error, and so on until the last estimation on [2261:3760]. For the data on OSESX index for the whole time period there were 227 rolling replications made and 227 estimates of  $\hat{\beta}$  and standard errors were reported. The result is presented on the plot 4. Since the first estimated  $\hat{\beta}$  was obtained from the [1:1500] observations, that is January 2000 – December 2005, estimated  $\hat{\beta}$  are traced from 2006 to 2014. The  $\hat{\beta}$  is sketched with 95% confidence interval boundaries that are represented by the red lines.

From plot 4 on the following page we can observe that the beta changes over time moving up and down with no systematic order. Moreover, the estimated beta reveals a tendency to decline over time, what could indicate a diminishing Weekend effect, if decline continues further. But for now the effect still remains significantly positive for the whole period.

It can be concluded that the tested OSE indices do not have a Weekend effect in its traditional form, that is, significantly small returns on Monday and significantly high returns on Friday, but there is evidence of significant high excess Friday returns in the OSESX Small Cap Index. It does not indicate that the market is inefficient, but the fraction of the market with the small firms exhibits predictable pattern, that leads to the less efficiency.

*Plot 4. Rolling regression estimation of the beta from the linear regression of the returns on the OSESX Small Cap index on Friday dummy.*



On the plot the blue line represents the  $\_b[F]$  which is the  $\hat{\beta}$  from the regression equation (13) which is the estimate of the parameter of Friday dummy. Lower and upper bounds (red lines) represent 95% confidence intervals for  $\hat{\beta}$ .

One of the possible explanations of persistence of the DOW effect in the small cap index is presence of transaction and information costs. As it was proposed by Kamara (1997), elimination of the seasonal anomaly is limited by transaction and information costs, since lower transaction and information costs enable traders to respond more actively to the anomaly. Keim and Madhavan (1995) found that the trading costs for institutions are largely lower for large stocks than for small stocks. This implies that institutional investors have more ability to trade out anomaly in the large cap stocks rather than in small cap stocks.

Typically, transaction costs faced by investors on the stock market can be described by bid-ask spread, brokerage fees, taxes and bank fees. The bid price is a price that one is willing to pay to buy a stock, whereas the ask price is a price that one is willing to sell the stock for. The bid-ask spread is a difference between two prices. For a highly liquid stock, the bid-ask

spread is narrow, buyer and seller agree upon a “right” price for the stock. For the less liquid stock, the bid-ask spread is found to be wide, that is common for less liquid small cap stocks.

On average, small cap stocks are traded not all trading days in the year, which contributes to higher volatility, that initiates a large dispersion in bid-ask spreads, so that stocks are set to be sold for a very high price. Thereby, a difference in transaction costs between large cap and small cap stocks is triggered by illiquidity of the small stocks, that is, it is not easy to convert small stocks into cash due to infrequent trading and therefore a broker may ask for higher compensation to deal with transaction, taking into account a large bid-ask spread. A magnitude of the transaction costs for the small cap stock prevents market players from trading out the anomaly documented in the small firms’ market section.

It was found in much research, that the excess returns caused by market anomalies, become normal returns after one accounts for the transaction costs. Once the transaction costs are excluded from the profits generated by abnormal returns, the anomaly becomes unprofitable.

### **5.2.2 Turn-of-the-month and intra-month effects**

Table 8 presents the results for the turn-of-the-month (TOM) and intra-month effects testing for pre- and post-crisis periods. The results for TOM effect are obtained from the estimation of the equation (5) and equation (6) and from the test results of the Kruskal-Wallis non-parametric test. For the intra-month effect, the results are obtained from estimation of equation (7).

From the results in table 8 for two periods it is evident that there is no intra-month effect in any tested indices, it is supported by the chi square test statistic of linear restrictions. This implies that the distribution of returns is equal for different parts of the month.

From the results on the TOM effect, there is indication of significant positive returns on the first trading day in the month, that is persistent for the returns on OBX and OSEAX indices and disappears in the post-crisis period for OSESX index. But, when regression with the bootstrap approach is applied on OBX and OSEAX indices returns for the post-crisis period, significance of the returns on the first trading day of the month disappears. In particular, chi squared test statistics at 5% significance level provide evidence of equality of returns on the first trading day in the month and the rest of the month. The test results from the regression with the bootstrap approach and chi square test statistics are not reported to avoid burdensome tables.

Table 8. Turn-of-the-month effect in the returns on the OBX, OSEAX, OSESX indices

	OBX		OSEAX		OSESX	
	<i>Pre-crisis</i>	<i>Post-crisis</i>	<i>Pre-crisis</i>	<i>Post-crisis</i>	<i>Pre-crisis</i>	<i>Post-crisis</i>
<b>-7</b>	-0.0000655 (0.963)	-0.0007798 (0.617)	-0.0002561 (0.846)	-0.000726 (0.582)	0.0000895 (0.930)	-0.0007297 (0.580)
<b>-6</b>	0.0014435 (0.327)	-0.0012941 (0.421)	0.0017621 (0.190)	-0.0005733 (0.673)	0.0004781 (0.653)	-0.0020697 (0.121)
<b>-5</b>	-0.0009195 (0.548)	0.0008523 (0.635)	-0.0010707 (0.462)	0.0007635 (0.615)	-0.0008913 (0.428)	0.0000433 (0.973)
<b>-4</b>	-0.0004751 (0.757)	-0.0000512 (0.975)	-0.0001721 (0.907)	-0.0003224 (0.819)	-0.0003294 (0.763)	0.0004424 (0.747)
<b>-3</b>	0.0005024 (0.722)	-0.0001776 (0.914)	0.0009336 (0.491)	-0.0001125 (0.933)	0.0015521 (0.142)	-0.0006551 (0.625)
<b>-2</b>	0.0006718 (0.647)	0.0001027 (0.955)	0.0010742 (0.424)	0.0002597 (0.863)	0.0007117 (0.507)	0.0010006 (0.477)
<b>-1</b>	0.0012872 (0.413)	-0.002174 (0.214)	<b>0.0024457</b> <b>(0.041)</b>	-0.0014756 (0.347)	<b>0.0032596</b> <b>(0.002)</b>	0.0006179 (0.659)
<b>+1</b>	<b>0.0057042</b> <b>(0.000)</b>	<b>0.0047098</b> <b>(0.002)</b>	<b>0.0054643</b> <b>(0.000)</b>	<b>0.0036604</b> <b>(0.006)</b>	<b>0.0019614</b> <b>(0.017)</b>	0.0002813 (0.835)
<b>+2</b>	0.0010715 (0.429)	-0.0013435 (0.432)	0.0012497 (0.322)	-0.0010669 (0.457)	0.0000929 (0.927)	-0.0012413 (0.366)
<b>+3</b>	-0.0006345 (0.653)	-0.0004537 (0.776)	-0.0004062 (0.758)	-0.0004636 (0.731)	-0.0010164 (0.322)	0.0005221 (0.694)
<b>+4</b>	0.0009196 (0.540)	0.0004821 (0.765)	0.0011895 (0.391)	0.0006171 (0.658)	0.0005786 (0.598)	0.0017944 (0.207)
<b>+5</b>	-0.0009722 (0.485)	-0.0006113 (0.715)	-0.00063 (0.629)	-0.0008817 (0.534)	0.0000887 (0.930)	-0.0014399 (0.292)
<b>+6</b>	-0.0015609 (0.297)	-0.0004216 (0.804)	-0.0006692 (0.630)	-0.0004321 (0.769)	-0.0006859 (0.506)	-0.0006896 (0.621)
<b>+7</b>	-0.000439 (0.774)	0.0013397 (0.428)	-0.0001492 (0.916)	0.0013653 (0.321)	-0.0001357 (0.898)	-0.0003848 (0.773)
<b>+8</b>	-0.0022515 (0.112)	-0.0018678 (0.252)	-0.0014319 (0.279)	-0.0014858 (0.274)	-0.0005268 (0.617)	-0.001004 (0.455)
<b>ROM<sub>t</sub></b>	0.0003407 (0.756)	0.0005873 (0.646)	0.0004462 (0.664)	0.000651 (0.552)	0.000376 (0.636)	-0.0003999 (0.711)
<b>Traditional TOM effect</b>						
<b>TOM<sub>t</sub></b>	<b>0.0018614</b> <b>(0.002)</b>	-0.0000617 (0.920)	<b>0.0019776</b> <b>(0.000)</b>	-0.0001207 (0.826)	<b>0.0010896</b> <b>(0.009)</b>	0.0002409 (0.631)
<b>Kruskal-Wallis test</b>	<b>9.450</b> <b>(0.0021)</b>	0.096 (0.7563)	<b>10.846</b> <b>(0.0010)</b>	0.108 (0.7420)	<b>10.320</b> <b>(0.0013)</b>	0.402 (0.5260)
<b>Intra-month effect</b>						
<b>FH<sub>t</sub></b>	0.000679 (0.086)	-0.0007384 (0.387)	0.0001224 (0.858)	-0.0006739 (0.374)	0.0001517 (0.577)	0.000363 (0.563)
<b>SH<sub>t</sub></b>	0.000572 (0.121)	-0.000608 (0.485)	-0.004114 (0.549)	-0.0004399 (0.568)	0.0002474 (0.442)	-0.000073 (0.907)
<b>χ<sup>2</sup> statistic</b>	0.36 (0.5476)	0.02 (0.8862)	1.43 (0.2317)	0.16 (0.6901)	0.95 (0.3289)	0.39 (0.5326)

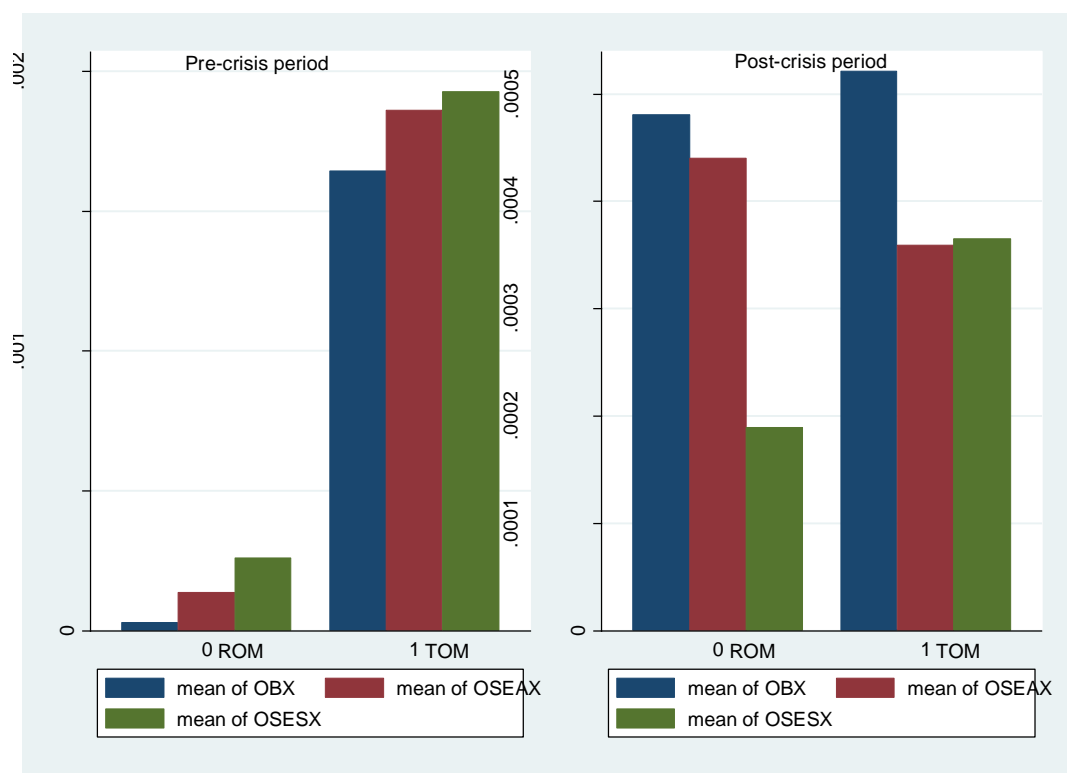
The table presents the results of estimation EGARCH(1,1)-t model with mean equation given by equations (5), (6) and (7) for the pre- and post-crisis periods. The columns contain estimated coefficients and p-value of z-statistics in the brackets. The bold figures represent the returns that are significant at 5% significance level. For the Kruskal-Wallis test results the test statistics and p-value in brackets are presented. The chi square statistics present results of testing  $H_0: FH_t = SH_t$ .



Moreover, the traditional TOM effect, that includes cumulative returns on the 4 trading days in the month, that is, a window of (-1, .., +3), and Kruskal-Wallis test results suggest that there was a presence of the TOM effect at OSE in the pre-crisis period, but this anomaly was not persistent and after the crisis occurred the distribution of returns became identical.

Plot 5 presents the mean of the returns on the OBX, OSEAX and OSESX indices for pre- and post-crisis periods for two groups: the first column presents mean of cumulative returns observed on the rest of the month, and the second column presents mean of cumulative returns observed on the turn of the month period. The plot certainly supports the results in table 8, the TOM effect in the pre-crisis period was apparent, with very low returns on the rest of the month compared to the TOM period. But for the post-crisis period, the magnitude of means become almost identical, especially for the OBX index returns, that can be an indication of diminishing anomaly.

*Plot 5. TOM effect at OSE in the pre-and post-crisis periods*



The first picture presents the TOM effect at OSE in the pre-crisis period, the second picture indicates the TOM effect in the post-crisis period. In both pictures, the first column is given by mean of returns on indices for the rest of the month and the second column indicates mean of returns for the TOM period, that is, for four trading days in the month, with the window (-1,..., +3).

From the results observed in this section, it can be concluded that TOM effect was present at the Oslo Stock Exchange in returns for all three indices, but the effect was short-term and disappeared after the crisis occurred. The conclusion indicates improving efficiency on the market and is consistent with market efficiency concept.

### **5.2.3 Turn-of-the-year effect**

Table 9 presents the results for the turn-of-the-year (TOY) effect in OSE indices, obtained by estimating equations (8) and (9).

For the pre-crisis period returns on the OBX and OSEAX indices exhibit no indication of the TOY effect, while in the post-crisis period there is evidence of significant positive returns on the first trading day in the year. But the results are not robust, since applied chi square test of linear restrictions for the estimated variables of the bootstrapped model do not provide evidence of difference in returns for the first trading day in the year and returns on the rest of the year. The bootstrapped model and chi square test results are not reported, but they are applied to check the robustness of result. Additionally, cumulative returns on traditional 6 days of TOY, obtained from estimation of the mean equation (9), do not reveal any difference compared to the returns observed on the rest of the year. These results are supported by the non-parametric Kruskal-Wallis test.

For the returns on the OSESX Small Cap Index the TOY effect reveals consistency, but in the post-crisis period it is represented only by positive high returns on the first trading day of the year. Kruskal-Wallis test results and the results obtained from estimation of equations (9) support evidence of a persistent TOY effect. This implies that cumulative returns on the 6 trading days indicating TOY effect, that is, a window of  $(-1, \dots, +5)$ , are significantly higher than returns observed on the rest of the year .

Also, there are some days in December for the OSESX index returns that are significantly different, but this can be probably explained by presence of the Holiday effect at the OSESX index, related to the Christmas period.

The TOY effect indicates that the small-cap firms outperform large-cap firms. From the results in table 9 it is evident that the returns during the TOY period for the OBX and OSEAX indices are not significantly different from returns during the rest of the year, while the OSESX Small Cap index returns revealed significantly high returns during the TOY period. This pattern indicates presence of the TOY effect at OSE, that distorts efficiency of the market.

Table 9. Turn-of-the-year effect on the OBX, OSEAX, OSESX indices' returns

	OBX		OSEAX		OSESX	
	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis	Pre-crisis	Post-crisis
<b><math>TD_{-7,t}</math></b>	-0.0031922 (0.357)	-0.000661 (0.863)	-0.0035918 (0.301)	0.0002138 (0.957)	<b>-0.0038509</b> (0.040)**	<b>0.0062842</b> (0.031)**
<b><math>TD_{-6,t}</math></b>	0.0044107 (0.380)	0.0039473 (0.329)	0.0055059 (0.194)	0.0063631 (0.081)*	<b>0.0052122</b> (0.037)**	<b>0.0072362</b> (0.016)**
<b><math>TD_{-5,t}</math></b>	-0.0031793 (0.627)	0.0033056 (0.632)	-0.0039256 (0.563)	0.0049868 (0.416)	-0.0005633 (0.942)	<b>0.0067248</b> (0.021)**
<b><math>TD_{-4,t}</math></b>	0.0028104 (0.663)	-0.0023453 (0.600)	0.0037192 (0.625)	0.0013708 (0.775)	0.0031944 (0.334)	0.0024599 (0.335)
<b><math>TD_{-3,t}</math></b>	0.0041987 (0.258)	0.004129 (0.461)	0.0020336 (0.564)	0.0042181 (0.458)	0.0027873 (0.253)	0.0036834 (0.206)
<b><math>TD_{-2,t}</math></b>	0.0060125 (0.144)	0.0012268 (0.803)	0.0072535 (0.050)*	0.0035193 (0.475)	0.0049123 (0.066)*	0.0046373 (0.297)
<b><math>TD_{-1,t}</math></b>	-0.0028765 (0.691)	-0.0060699 (0.369)	-0.0004457 (0.947)	-0.0041323 (0.451)	0.0023233 (0.550)	0.0014727 (0.581)
<b><math>TD_{+1,t}</math></b>	0.0063041 (0.185)	<b>0.009852</b> (0.000)***	0.0054965 (0.262)	<b>0.0128482</b> (0.001)***	<b>0.0100928</b> (0.002)***	<b>0.005889</b> (0.026)**
<b><math>TD_{+2,t}</math></b>	-0.0028029 (0.242)	-0.0014982 (0.703)	-0.0025936 (0.219)	0.0016475 (0.741)	0.0000732 (0.969)	-0.0008321 (0.758)
<b><math>TD_{+3,t}</math></b>	-0.0043533 (0.073)*	-0.0009812 (0.851)	-0.0044842 (0.074)*	-0.0006049 (0.916)	<b>-0.0067631</b> (0.002)***	0.000411 (0.924)
<b><math>TD_{+4,t}</math></b>	-0.0025131 (0.736)	-0.0020571 (0.697)	-0.0021905 (0.728)	0.0009213 (0.920)	0.0011856 (0.680)	0.0031213 (0.408)
<b><math>TD_{+5,t}</math></b>	0.0012966 (0.709)	0.0020672 (0.728)	0.0005655 (0.872)	0.0010563 (0.884)	0.0030727 (0.147)	0.0026943 (0.482)
<b><math>TD_{+6,t}</math></b>	0.0005877 (0.889)	0.002593 (0.641)	0.0012256 (0.739)	0.0005176 (0.917)	0.0031048 (0.344)	0.0016591 (0.679)
<b><math>TD_{+7,t}</math></b>	-0.0043209 (0.264)	0.0022609 (0.458)	-0.0031433 (0.353)	0.0056543 (0.229)	-0.0018032 (0.463)	-0.0001816 (0.393)
<b><math>TD_{+8,t}</math></b>	-0.0002641 (0.949)	0.0011606 (0.808)	-0.0009441 (0.830)	-0.0006003 (0.910)	0.0031013 (0.266)	0.0015888 (0.606)
<b>Traditional TOY effect</b>						
<b>TOY [-1:+5]</b>	0.0002775 (0.847)	-0.0001088 (0.940)	0.0007318 (0.593)	0.0001094 (0.932)	<b>0.0027057</b> (0.006)	<b>0.002044</b> (0.045)
<b><math>\chi^2</math> statistic</b>	0.01 (0.9346)	0.22 (0.6424)	0.10 (0.7574)	0.18 (0.6744)	<b>6.90</b> (0.0086)	<b>4.15</b> (0.0417)
<b>Kruskal-Wallis test</b>	0.190 (0.6625)	0.288 (0.5914)	1.497 (0.2211)	0.526 (0.4683)	<b>15.701</b> (0.0001)	<b>10.860</b> (0.0010)

The estimated coefficients are obtained from the estimation of mean equations in EGARCH(1,1)-t model, given by equations (8) and (9). The results are given by estimated coefficient and p-value of z-statistics in brackets. The bold numbers present coefficients that are significant at 5% significance level. Chi square test provide results of testing the hypothesis  $H_0$ : returns on the TOY period = returns on the rest of the year. For Chi square and Kruskal-Wallis tests, test statistics and p-value in the brackets are provided.

## 5.2.4 Holiday effect

Table 10 provides results of the estimation of equations (10), (11) and (12) for three pre-holiday days. The obtained results provide no evidence of the holiday effect in the OBX and OSEAX indices for two periods, whereas for the returns on OSESX index there is evidence of the pre-Christmas effect, which is stronger in the post-crisis period. Also, the results of estimated bootstrapped model and applied chi squared test verify presence of the pre-Christmas effect in the OSESX index returns for both tested periods at 5% significance level, meaning that returns are significantly high on the last trading day before Christmas. The results are not reported to avoid burdensome tables. This results are complementary to the one, obtained in table 9, where returns on OSESX index indicate significance for some days in December in both periods.

*Table 10. Estimated results for the Holiday effect on OSE indices' returns*

	<b>OBX</b>		<b>OSEAX</b>		<b>OSESX</b>	
	<b>Pre-crisis</b>	<b>Post-crisis</b>	<b>Pre-crisis</b>	<b>Post-crisis</b>	<b>Pre-crisis</b>	<b>Post-crisis</b>
<b>Christmas</b>	0.0017709 (0.710)	0.0048129 (0.341)	0.0001586 (0.972)	0.0052772 (0.198)	0.0035118 (0.296)	<b>0.0063098</b> <b>(0.008)</b>
<b>Kruskal-Wallis test</b>	1.755 (0.1852)	2.477 (0.1155)	1.203 (0.2728)	3.447 (0.0634)	<b>4.087</b> <b>(0.0432)</b>	<b>5.447</b> <b>(0.0196)</b>
<b>Easter</b>	0.0008739 (0.798)	0.0044849 (0.305)	0.0018316 (0.583)	0.0060414 (0.145)	0.0038744 (0.173)	0.0048446 (0.373)
<b>Kruskal-Wallis test</b>	0.269 (0.6038)	0.830 (0.3624)	0.344 (0.5573)	0.863 (0.3528)	2.260 (0.1327)	1.057 (0.3039)
<b>Norwegian Constitution day</b>	0.0025689 (0.565)	-0.0009961 (0.874)	0.0018072 (0.544)	-0.0012802 (0.830)	-0.0006043 (0.842)	-0.0018449 (0.599)
<b>Kruskal-Wallis test</b>	0.536 (0.4641)	1.117 (0.2906)	0.780 (0.3771)	1.592 (0.2070)	0.449 (0.5028)	1.057 (0.3039)

The table contains estimated coefficients and p-values of z-statistics in the brackets. For the Kruskal-Wallis test, the chi squared test statistics and p-value in the brackets are provided.

In conclusion, the results in table 10 reveal that there is no Holiday effect in the market per se and in the part of the market represented by firms with the most liquid stocks, but there is presence of the holiday effect, in particular pre-Christmas effect, in the part of the market with small cap firms, which makes this part of the market less efficient.

One of the explanations of persistence of anomaly in OSESX index returns is high transaction costs, the same what perhaps contributed to the persistence of other detected in the small cap index calendar anomalies.

## Conclusion

The results from the calendar anomalies testing suggest that detected calendar anomalies for returns on the OBX and OSEAX indices are short-term, whereas anomalies found in the returns on the small cap index are persistent, indicating less efficiency of this part of the market and opportunity to profit from exploitation of anomalies.

Generally, two definitions of market efficiency can be applied when consider calendar anomalies. The first definition relate to the wide definition, that states that one cannot earn excess returns after transaction costs are taken into account. And the second definition is narrow, it states that one cannot theoretically earn excess returns. The second definition disregards transaction costs. This makes most anomalies found on the market profitable, whereas it could not be a case once transaction costs are excluded. If we consider the narrow definition of market efficiency, it would be relevant to conclude upon inefficiency of part of the market represented by small cap companies, since test results provide evidence of presence of persistent anomalies in the small cap index, in particular, the Weekend, Turn-of-the-year and Holiday effects. However, persistence of the calendar anomalies in the returns on the small cap index is opposed by results for the returns on the OBX and OSEAX indices, where anomalies detected in the pre-crisis period were short-term, and did not appear in the post-crisis period, indicating efficiency of the market. Perhaps persistence could be explained by high transaction costs due to infrequent trading, which make anomaly unprofitable, so that investors do not trade it out as time go on. In this case, the wide definition of market efficiency would be appropriate. Thus, with application of this definition we may challenge the conclusion of inefficiency of small cap part of the market, since we do not have a strong evidence of the excess returns, that is, returns after the transaction costs are excluded, to exhibit detected calendar anomalies, what would provide an opportunity to profit from anomalies.

Thereby, it is reasonable to conclude that the part of the market represented by small cap firms exhibit less efficiency than the parts of the market represented by firms which stocks are listed on the OBX and OSEAX indices.

## 6 Conclusion

In this thesis, weak form of market efficiency and calendar anomalies at the Oslo Stock Exchange were investigated. The Oslo Stock Exchange was described by the OBX Total Return Index, the OSEAX Oslo Børs All Share Index and the OSESX Oslo Børs Small Cap Index, that characterize the part of the market with the most liquid firms, whole market per se and the part of the market with small cap firms respectively. The tested period represents 14 years of observations, namely January 2000-December 2014, which are divided in two sub periods represented by pre- and post-crisis periods.

First, the weak form of market efficiency was tested with application of the variance ratio, unit root and autocorrelation tests. The results from the random walk hypothesis testing, that is, variance ratio test and unit root test, support the random walk hypothesis for the closing prices on the OBX and OSEAX indices, indicating that these parts of market are weak form efficient, with OSEAX index exhibiting improving efficiency in the post-crisis period. The results for the OSESX index provide evidence to reject the random walk hypothesis, mainly due to the presence of serial correlation, whereas unit root test support the hypothesis of closing prices on OSESX index to have a unit root. Serial correlation in OSESX index returns has a tendency to lessening, it reduced in the period observed after the 2008-2009 crisis. Furthermore, the observed dependency in the small cap index returns may not provide opportunity to gain from it, due to small autocorrelation coefficients. As it was suggested by Lo and MacKinlay (1988), possible cause of positive serial correlation in returns on the small cap index is infrequent trading, stocks of the firms listed on the small cap index are on average traded not all trading days in the year. Infrequent trading causes the information to not immediately being reflected into the price of the small stock. The information is impounded into the small stocks with a lag after it is reflected in the large stocks. This lag creates a positive serial correlation in the small cap stocks. Thereby, the part of the market represented by small cap companies is less efficient.

Investigation of the presence of calendar anomalies in the market also revealed less efficiency of the small cap index. Returns on the OBX and OSEAX indices exhibit absence of calendar anomalies or improving market efficiency, when compare results between two periods. The OSESX index returns exhibit presence of the persistent anomalies such as day-of-the-week effect, namely large abnormal returns on Friday, turn-of-the-year effect and holiday effect, in particular, pre-Christmas effect.

Possible explanation of persistence of detected anomalies in the small cap index is presence of high transaction and information costs in the market. As it was suggested by Kamara (1997) low transaction costs enable traders to respond more actively to anomaly, thus competing it out. Furthermore, Keim and Madhavan (1995) found that trading costs for institutions are lower for large cap stocks than for small cap stocks. This implies that institutional investors have more ability to trade out anomaly in the large cap stocks rather than in the small cap stocks. Presence of high trading costs makes gains from exploitation of anomalies significantly smaller, which prevents investors from trading out the anomaly.

It can be concluded that the Oslo Stock Exchange is weak form efficient, and exhibits no seasonal predictable patterns in the part of the market represented by the companies listed on the OBX and OSEAX indices, that is, the part of the market represented by companies with the most liquid securities and all companies listed on Oslo Børs. But the part of the market represented by small cap companies displays less efficiency and persistent seasonal anomalies, that perhaps cannot be traded out due to presence of high trading costs.

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